Coordination of Concurrent One-to-Many Negotiations in Multi-Agent Systems

Khalid Mansour

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Faculty of Science, Engineering and Technology
Swinburne University of Technology

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to my parents

Abstract

Automated negotiation is a key interaction mechanism in distributed and multi-agent systems. By adapting negotiation as an interaction method, autonomous agents can interact, compete and cooperate with one another effectively. When the scale of negotiation expands to involve more than two agents, the negotiation process becomes more complex. This thesis addresses the problem of managing concurrent and dependent instances of automated negotiations in the one-to-many multi-agent systems where agents are self-interested, unwilling to disclose their private information (e.g., utility structure, deadline, etc.) and the available information about the opponents is mainly the current history of their offers. In particular, this thesis considers the one-to-many negotiation where a buyer agent negotiates with multiple seller agents over one or more objects concurrently. Dependent instances of negotiation occur when different negotiations are related and the situation of one instance affects the situation of one or more other instances.

The main challenge of this thesis was to investigate the bidding strategy for a buyer agent negotiating concurrently with multiple seller agents over one or more negotiation objects where each object can be characterized by one or more issues (attributes.) Most of the current works in the literature target simple one-to-many negotiations where agents negotiate a single negotiation issue. A few works investigate the case where agents negotiate multiple issues. The work in this thesis proposes new negotiation techniques to further improve the existing ones. In addition, more complicated negotiation scenarios are investigated where agents negotiate over multiple objects with single or multiple negotiation issues.

The first step in the proposed solution approach is to analyze the one-to-many negotiations illustrating how different numbers of negotiation components can affect the course of the coordination mechanism in each negotiation scenario. In the context of this thesis, the negotiation components are: negotiation objects, negotiation issues and agents. Considering the different negotiation scenarios that can arise from the combination of different numbers of the negotiation components, appropriate mechanisms and algorithms are proposed to solve the relevant coordination problem in different negotiation scenarios. Defining different negotiation scenarios depend on the number of negotiation objects, the number of negotiation issues per object and the number of

opponent agents per object. The number of each component can be either single or multiple. Since the one-to-many negotiation is considered in this thesis, the number of opponents is always multiple. Considering the behaviors of the opponent agents that are still in negotiation, this thesis proposes effective coordination solutions that involve determining the value of the next counteroffer the buyer agent needs to propose to each seller agent in each negotiation round.

Five one-to-many negotiation scenarios are recognized and named *coordination scenarios*. Coordinating the bidding strategy for a buyer agent in the five coordination scenarios is the main focus of this thesis. This work advances the state of the art by analyzing different negotiation scenarios and proposing novel mechanisms that improve and further extend the existing work to solve more complex negotiation scenarios.

The main approach adopted in solving the coordination problems in the one-to-many negotiation is to change the negotiation strategy during negotiation (i.e., in real-time) in response to the current behaviors of the opponents in terms of their concessions. For example, the convexity of a concession curve is one of the parameters of a negotiation strategy. If the convexity of a concession curve can be dynamically controlled during negotiation, then a particular coordination problem can be solved. Since different coordination scenarios have different numbers of components and related variables, then different coordination mechanisms are necessary to deal with different coordination scenarios. For example, when an agent negotiates with multiple other agents over one object characterized by one issue (e.g., price), then the agent can use a coordination mechanism that manages the convexity of its concession curve(s) to maximize its utility. In this case, the agent cannot consider other cooperative solutions such as the trade-off mechanism.

Experiments that compare between the proposed negotiation strategies and the state-of-the-art strategies are used to test the effectiveness and robustness of the proposed solutions empirically. The main performance criteria in the experiments are the agreement rate and the utility rate. In most cases, the results of the experiments prove that the proposed solutions to the coordination problems in different coordination scenarios are effective and robust in terms of both, the utility rates and the agreement rates. In scenarios where there is room for cooperation e.g., in case of multi-issue negotiation, the proposed techniques consider also the social welfare and the fairness of an agreement as performance criteria.

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Declaration

This thesis contains no material which has been accepted for the award of any other degree or diploma, except where due reference is made. To the best of my knowledge, this thesis contains no material previously published or written by another person except where due reference is made in the text of the thesis.

Khalid Mansour

Khalid Mansour

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Publications

Parts of the material presented in this thesis have previously appeared in most of the following publications:

1. K. Mansour and R. Kowalczyk. An Approach to One-to-Many Concurrent Negotiation. *Group Decision and Negotiation*. (Accepted for publication on 27/01/2014). **Impact factor: 0.897**

2. K. Mansour and R. Kowalczyk. An Approach for Coordinating the Bidding Strategy in Multi-Issue Multi-Object Negotiation with Multiple Providers. *IEEE Transactions on Systems, Man, and Cybernetics, Part B*. (First revision was submitted on 09/09/2013). **Impact factor: 3.236**

3. K. Mansour, R. Kowalczyk, and M. Wosko. Aspects of Coordinating the Bidding Strategy in Concurrent One-to-Many Negotiation. *In Knowledge Engineering and Management*, 103-115, 2014, Springer.

4. K. Mansour and R. Kowalczyk. On Dynamic Negotiation Strategy for Concurrent Negotiation over Distinct Objects. In Marsa-Maestre, I.; Lopez-Carmona, M.A.; Ito, T.; Zhang, M.; Bai, Q.; Fujita, K. (Eds.). *Novel Insights in Agent-based Complex Automated Negotiation*, Vol 535, 2014, Springer.

5. M. Wosko, I. Moser, and K. Mansour. Scheduling for Optimal Response Times in Queues of Stochastic Workflows. *Lecture Notes in Computer Science*, 8272:502-513, 2013, Springer.

6. K. Mansour and R. Kowalczyk. On Dynamic Negotiation Strategy for Concurrent Negotiation over Distinct Objects. *The 5th International Workshop on Agent-Based Complex Automated Negotiations (ACAN) at AAMAS*, 65-72, 2012.

7. K. Mansour. Managing Concurrent Negotiations in Multi-agent Systems. *Lecture Notes in Artificial Intelligence*, 7310:380-383, 2012, Springer.

8. K. Mansour, R. Kowalczyk, and M. B. Chhetri. On Effective Quality of Service Negotiation. *In the 12th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing*, 684-685, 2012.
9. K. Mansour, R. Kowalczyk, and M. Wosko. Concurrent Negotiation over Quality of Service. *In the Proc. of the IEEE Ninth International Conference on Services Computing*, 446-453, 2012.
10. K. Mansour and R. Kowalczyk. A Meta-Strategy for Coordinating of One-to-Many Negotiation over Multiple Issues. In Y. Wang and T. Li, editors. *Foundations of Intelligent Systems*, 343-353, 2011, Springer.
11. K. Mansour, R. Kowalczyk, and B. Q. Vo. Real-Time Coordination of Concurrent Multiple Bilateral Negotiations under Time Constraints. *Lecture Notes in Artificial Intelligence*, 6464:385-394, 2010, Springer.

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Chapter 1

Introduction

Negotiation is prevalent in our daily life as a method of conflict resolution. Negotiation is a major mechanism of interaction and decision making in many important domains such as politics, law, sociology, business and personal situations (e.g., [75][64][130]). In particular, negotiation can be looked at as a process of distributed decision making amongst two or more parties who seek to agree upon a conflicting matter [61]. The negotiation theory has been investigated from different perspectives such as game theory [47] and decision-analytic approach [116].

The tremendous advances in the web technology and networking have opened a new era for the application of automated negotiation where software agents or autonomous computer systems are able to automate some aspects of the negotiation process. Automated negotiation has been an active research area for more than a decade (e.g., [2][32][33][39]). As negotiation is an effective mechanism for decision making and conflict resolution, the automation process of negotiation aims for better negotiation results in terms of utility gain, agreement rate, social welfare and fairness. In addition, the automation of the negotiation process aims to enable software agents to work on behalf of the users to reach agreements quickly with the best possible outcome. Moreover, the automation of negotiation enables agents to negotiate complex contracts more efficiently than humans do. Complex contracts may contain a large number of issues that can be either interdependent or independent.

Negotiation is one of the coordination approaches that can be used to coordinate various activities amongst different parties such as scheduling and resource allocation (e.g., [153] [55]). However, the main focus of this thesis is the problem of coordinating the bidding strategy for a buyer agent conducting multiple negotiations simultaneously. The multiple concurrent negotiations are assumed to be interdependent since all negotiations share a common goal(s) and a common resource(s). The resources are managed in a way to achieve the common goal(s). For example, if the common goal is to reach an agreement with a high utility then the resources (e.g., money) are dynamically allocated during negotiation amongst the multiple negotiations to help achieve the specified goal.

Even though the proposed negotiation model, the proposed coordination mechanisms and the experimental results present a buyer agent's point view, the negotiation model is general and can present a seller agents' point of view as well. In addition, the proposed coordination mechanisms can still be used by a seller agent. However, the seller agent might also consider other factors when using the proposed mechanisms, such as reputation.

A few existing works in the literature address the aspects of the coordination problem in the one-to-many negotiation. However, most of the related works focus on simple negotiation scenarios where agents aim to negotiate a single issue. In addressing the problem, we use the divide and conquer strategy to tackle it systematically through different scenarios. The cardinalities of negotiation *objects*, negotiation *issues* per object and *providers/opponents* per object are considered the main negotiation criteria and are used to define different negotiation scenarios. For example if the cardinality for the set of agents is 2, then the negotiation is of a bilateral type.

A subset of the negotiation scenarios is highlighted and named *coordination scenarios*. It encompasses all the one-to-many negotiation variants that are determined by the negotiation components mentioned in the previous paragraph. Each coordination scenario is characterized by a unique combination of a number of distinct objects, a number of issues per object and a number of providers per object. For example, if a buyer agent seeks to procure a storage space, a software application and a certain computational power from the cloud, given that all specifications are agreed upon apart from the price, then the buyer agent needs to negotiate the price of each service with one or more providers. This scenario is characterized by multiple negotiation objects (e.g., storage space) given that each object has one negotiation issue (e.g., price) and multiple providers. If the number of negotiation issues per object is multiple, then a different coordination scenario arises.

For each different coordination scenario, one or more negotiation parameters are selected to be controlled or adapted during negotiation. The adaptation of a certain negotiation parameter reflects the behaviors of the current opponents in terms of their concessions in the current negotiation encounter. For example, the convexity of the concession curve is one of the parameters that can be managed during negotiation. To validate the proposed solutions, experiments are designed and implemented to compare between the performance of the proposed solutions and other benchmark solutions in terms of the utility rates, agreement rates, social welfare etc.

The bilateral negotiation is the basic form of negotiation where two agents exchange offers and counteroffers. Different game theoretic and artificial intelligence (*AI*) mechanisms have been proposed in the process of decision making during negotiation (e.g., [13] [12] [163] [6]). However, it is difficult to apply the game theoretic approaches in real negotiations since they typically require that the two negotiation partners disclose their preference profiles which is an unrealistic assumption due to privacy and trust issues. In most cases, the *AI* mechanisms are heuristic approaches that require either historical data or use learning mechanisms that need considerable computational power and time. When it comes to making a decision in the one-to-many negotiation, the situation becomes even more complicated since there are multiple interactions between multiple agents.

The mediated negotiation is a negotiation approach where two or more agents negotiate using a mediator (e.g., [79][31]). The approach requires that agents send their proposals to the mediator. The participating agents need also to disclose all or some of their preference profiles to the mediator. The mediator uses the collection of profiles and attempts at finalizing an agreement that is fair and acceptable for all parties. The trust and privacy matters are the main obstacles in adopting the mediated negotiation approach.

The proposed mechanisms in this thesis do not require historical data. As a source of information, they rely only on the offers received from the opponents during the current negotiation. Finally, the negotiation strategy components that are considered in this thesis are: the reservation value and the set of negotiation tactics with their parameters. A dynamic negotiation strategy may change the value of any of these parameters during negotiation to accommodate a new negotiation situation.

1.1 Problem Description

When a software agent interacts with other software agents through negotiations, it needs to decide the values of the proposals in every negotiation round. In other words, the agent needs to have a bidding strategy that enables it from taking appropriate decisions regarding the values of the proposals in every negotiation round.

This research aims at advancing the state-of-the-art in the process of automation of negotiation and particularly it focuses on the problem of coordinating the bidding strategy for multiple concurrent one-to-many negotiations in multi-agent systems. The bidding strategy controls the process of generating offers and counteroffers. The bidding strategy and negotiation strategy are used interchangeably in this thesis. A negotiating agent needs to coordinate its concurrent multiple negotiations when interacting with multiple agents to improve one or more performance criteria. The key point in solving any coordination problem is the ability to manage dependencies between related activities [84]. In other words, the dependencies between the different related activities cause the coordination problem. The activities of an agent in the negotiation context mean all possible actions that can be taken by an agent as defined by a negotiation protocol. For example, proposing an offer with a certain value and accepting an agreement are examples of possible actions during negotiation. Given that a negotiation strategy consists of a set of parameters with certain values, the coordination problem is to define a value for each parameters dynamically during negotiation.

The proposed coordination mechanisms (decision making mechanisms) depend on the behaviors of the current opponents in terms of their concessions. The concessions of the negotiating agents affect the coordination mechanisms that decide the proposal values in the next negotiation round. Taking into consideration the concessions offered by the negotiating agents in the previous negotiation round(s), one or more negotiation parameters can be changed by the coordination mechanisms. The convexity of the concession curve is one of the negotiation strategy parameters than can be manipulated during negotiation. Chapter 4 contains more details about the coordination problem and the solution approach.

1.2 Usage Scenarios

This work mainly investigates the bidding strategy problem in one-to-many automated negotiation. Ma and Leung in their book titled 'Bidding Strategies in Agent-Based Continuous Double Auctions' wrote [82]:

> *Automation of bidding is complex. Given the variety of auction protocols, it is perhaps not surprising that the bidding strategies of the participants cover a similarly broad spectrum of behaviors. In short, there is no optimal strategy that can be used in all cases. To be effective, bidding strategies need to be tailored to the type of the auction in which they are to be used. Perhaps the key challenges in this area is to design effective and efficient strategies that agents can use to guide their bidding behavior.*

Deciding on a bidding strategy in the one-to-many negotiation is a nontrivial problem since an agent needs to analyze the behaviors of the opponents and reply to each one of them and/or to each group of them differently. It is even more complex than the bidding strategy in auctions since the auctions assume bidding on one issue (mainly price) in most cases. The one-to-many negotiation applies to many real life interaction scenarios. The electronic commerce is a potential application domain for the agent-mediated with fully automated negotiation [132]. To motivate this research, three potential application scenarios are presented. The first one shows how the one-to-many negotiation can reduce cost and/or improve the efficiency of the *scientific workflows execution*. The second one presents the *holiday booking* scenario and how the one-to-many negotiation helps travelers find good deals while the third application scenario shows how automated negotiation can help in the process of supply chain management.

1.2.1 Scientific Workflow in the Cloud Scenario

Many scientific applications nowadays are highly demanding for both computational and storage resources [152][26]. For example, the astrophysics applications process large amounts of data such as pulsar searching which is a scientific application that processes terabytes of data [26]. The pulsar searching has a workflow of processing the raw data collected from the telescope and preparing it for decision making. Such scientific workflows produce large amount of intermediate datasets and require intensive computational power. The generated intermediate datasets are needed either for generating of other intermediate datasets or for analysis. The intermediate datasets are interdependent since an intermediate dataset requires one or more other datasets for its generation. Figure 1.1 shows a dependency example amongst a group of datasets. In Figure 1.1, dataset 1 (dt1) is required to generate both dt2 and dt3, while dt2 is required to generate dt4 and dt5 etc.

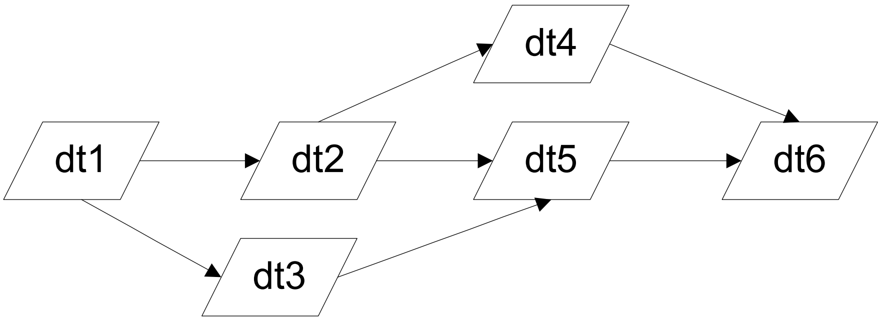


Figure 1.1: *Data set generation workflow*

When dealing with such scientific workflows, the problem of deleting or storing the intermediate datasets comes in place. When running such scientific workflows on the cloud, the problem of limited storage and computational resources can be avoided since the cloud provides, theoretically, unlimited resources. While executing a scientific workflow in the cloud, an application needs to use computational power or storage space throughout the execution of the workflow. To improve the utilization of resources on the cloud in terms of both the cost and efficiency of producing a needed dataset from another predecessor dataset(s) during the execution of a certain workflow, we propose provisioning computational power and/or storage space during the execution of the workflow using automated negotiation in real-time. For storage power, agents can negotiate: storage size, price and length of the storage period etc. For computational power, agents can negotiate: price, computational speed, etc. In some cases, some software is needed to execute certain tasks.

During negotiation, when the customer agent receives several offers from different service providers, it analyzes the value of the received offers along with its own preference profile and makes appropriate decisions regarding accepting, rejecting or counteroffer proposing. It is the objective of this thesis to develop decision making mechanisms that enable the consumer agent to take effective negotiation decisions in real-time during negotiation. Using automated negotiation in the cloud has the following advantages:

1. A scientific workflow may not know in advance the future computational and storage resources needed. Instead of buying resources before starting the workflow, an agent can negotiate with the providers of cloud resources to provision resources in real time. In this case the workflow will use the minimum needed resources during its execution.

2. Since there are multiple resource providers in the cloud, automated negotiation in real-time takes the advantage of existing multiple providers in increasing the bargaining power of the buyer negotiator.

3. During negotiation, the workflow controller can decide whether to store a certain dataset or delete a dataset depending on the received offers from the resource providers.

As the cloud computing provides a set of computational resources, the buyer agent can negotiate with different resource providers in the cloud during processing scientific data, see Figure 1.2.

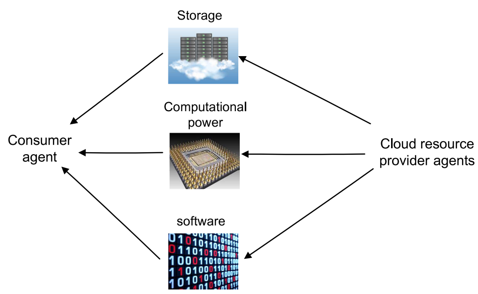


Figure 1.2: *Resources on the cloud*

This thesis proposes a general negotiation model that considers each resource, service or an item as an object. A buyer agent may require different objects at a certain point of time. Each object can be characterized by one or more issues. Most of the related works in the literature consider simple scenarios where agents negotiate over a single object, e.g., a cloud resource. The work in this thesis improves the current bidding strategies of simple scenarios and proposes more effective bidding strategies for more complex negotiation scenarios where the number of the required objects are multiple.

1.2.2 Holiday Booking Scenario

This scenario is well known in the service oriented domain (e.g., [96][7][98]) where a customer seeks a holiday package including a flight, a hotel and a car, see Figure 1.3. The automated one-to-many negotiation is a flexible approach for provisioning a holiday package. It is known that travelers prefer certain dates and travel times, have certain preferences over hotel bookings, such as hotel location (e.g., within a city or outside the city) and hotel rating, e.g., 5 star hotel. For choosing a car, the traveler may have certain preferences over the model and make of the car, its color etc. The price can be one of the important issues but not the only one. Figure 1.3 shows that each service has multiple attributes (issues) to be negotiated over between a traveler and service providers.

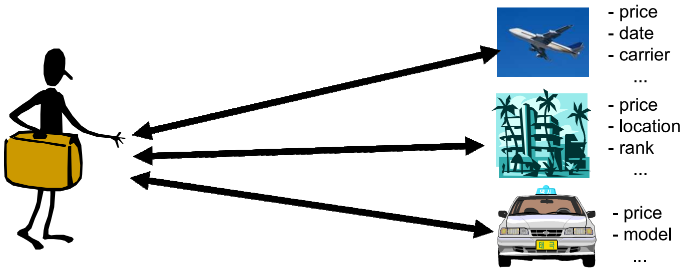


Figure 1.3: *Travel booking scenario*

The auction models for service provisioning are not flexible since they focus on one negotiation issue (usually price) and provide a limited number of predefined packages. As Figure 1.3 shows, each service can have multiple negotiation issues. In addition, each service can have multiple providers. The one-to-many negotiation allows a customer agent to interact with different service providers concurrently. A negotiating agent who receives multiple offers from service providers can analyze the received offers and determine its next decision, either to accept one of the received offers or to offer a new proposal. The coordination problem in that context is to find the best match between the issue values of the different services taking into consideration the preference profile of the customer agent and the value of the received proposals.

Most of the related works do not consider negotiation over multiple objects (e.g., services) concurrently. This thesis proposes effective negotiation strategies for a buyer agent negotiating concurrently with multiple seller agents over multiple objects.

1.2.3 Supply Chain Scenario

A supply chain consists of all the intermediate points between the raw materials and customers through which raw materials are acquired, processed, and delivered [44]. For example, the intermediate points can be: suppliers, warehouses, factories, etc.

Using a mediator agent to help in the negotiation process between two agents representing two firms is proposed in [41] where the negotiating agents aim to coordinate their production sequences. Duan et al. propose a negotiation framework to tackle the supplier-manufacturer problem where agents negotiate on the delivery schedules. The issues of negotiation can include time, quantity and price [28]. The authors consider that the delivery schedules for the supplier-manufacturer form an integral part of an agent's local optimization problem.

Supply chain management is a critical task for business success. As supply chain management is concerned with the moving of material in a consistent manner, material procurement is an essential part of the supply chain management. Figure 1.4 shows that a factory, which can be represented by a buyer agent, interacts with three sources of raw materials that can be represented by three raw material seller agents. The raw material can contain negotiation issues such as price, quantity, delivery date etc.

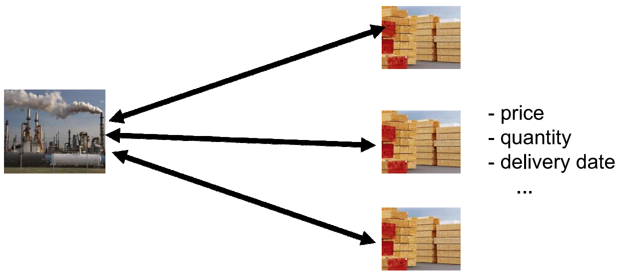


Figure 1.4: *Supply chain*

Adopting the one-to-many negotiation model for solving the material procurement problem in the supply chain can empower customers where there are multiple suppliers in the market. In this case, when the customer negotiates with multiple suppliers, the customer can benefit from the different proposals received from the suppliers by either accepting the best proposal or offering new proposals. This thesis aims to empower the customer agent by providing it with the appropriate decision making mechanisms in such scenarios.

Just-in-time (*JIT*) manufacturing is a managerial philosophy that depends on procuring the only needed materials or parts for running manufacturing processes. The *JIT* manufacturing reduces both, the amount of inventory and the amount of waste [147]. When the *JIT* model is used by a manufacturing system, automated negotiation can add a value to the *JIS*. When a certain amount of material or some parts are needed by a manufacturing system, the system conducts concurrent negotiations with a number of suppliers to negotiate critical issues such as quantity, price and delivery time of the required parts or material. Introducing the automated negotiation in the *JIF* automates the process of procuring materials which improves the efficiency and the effectiveness of delivering the right materials at the right time.

As the case with the previous two sections, most of the related works in the literature consider the problem of a single object of a single issue negotiation. In case of the supply change management, most negotiations involve multiple issue negotiation or multiple object negotiation. This thesis improves the current negotiation mechanisms of simple scenarios and presents novel algorithms to handle complex negotiation scenarios.

1.3 Research Questions

Since the objective of this thesis is to investigate the coordination problem in the one-to-many negotiation in multi-agent systems under the assumptions that agents do not disclose their private information and the only available information for an agent during negotiation is the offers received from its current opponents, this thesis addresses the following main research question:

Can the bidding strategy for multiple concurrent one-to-many negotiations be coordinated by adapting an agent's negotiation strategy parameters during negotiation?

The main question can be subdivided into the following research question:

1- **Convexity of the Concession Curves:** the convexity degree of a curve determines its slop at a certain point. Changing some parameter of the curve equation can change its slop. In the time-dependent offer generation tactics [33], changing the β value results in changing the convexity of the concession curve. The first subquestion can be formulated as follows.

- Can the approach of adapting the **convexity of concession curves** during multiple concurrent negotiations be an effective method in improving one or more of the negotiation performance criteria?

2- **Negotiation Meta-Strategy:** a meta-strategy is a strategy that uses more than one type of negotiation tactic. For example, the concession and trade-off are two different negotiation tactics that can be used during negotiation according to some rules. The second subquestion can be formulated as follows.

- Can the approach of **alternating between different negotiation tactics** during multiple concurrent negotiations be an effective approach in improving one or more of the negotiation performance criteria?

3- **Local Reservation Values:** the local reservation values refer to the reservation values of the *common issues* of different negotiation objects. We assume that the global reservation value of *common issues* is fixed throughout negotiation while it is possible to update the local reservation values of the *common issues* of certain negotiation objects as a response to some changes in the negotiation environment. The third subquestion can be formulated as follows.

- Can the approach of adapting the **local reservation values** during multiple concurrent negotiations be an effective method in improving one or more of the negotiation performance criteria?

4- **Multi-Level Coordination:** When an agent negotiates over multiple objects given that each object has multiple providers, then the agent needs to analyze the behaviors of all opponents over all objects (global coordination level) and analyze the behaviors of opponents over each particular object which is the local coordination level. For each coordination level, the agent controls one or more negotiation strategy parameters in the coordination process. The fourth subquestion can be formulated as follows.

- Can the approach of **managing negotiation strategies at both, the global level and local level** during multiple concurrent negotiations be an effective method in improving one or more of the negotiation performance criteria?

The answers to the research questions are discussed in chapter 8.

1.4 Contributions

The dynamic coordination in concurrent one-to-many negotiation involves managing the negotiation strategy dynamically during negotiation for multiple instances (interactions) of concurrent negotiations. The main body of this work investigates the dynamic bidding strategy in one-to-many negotiation. The bidding strategy determines how an agent calculates the value(s) of its next offer(s). The proposed coordination approach considers the level of cooperation of the opponents in the terms of their offered concessions in the current negotiation interaction. The previous data about the past negotiations are not considered. The reason is that agents can be situated in dynamic environments and their goals can be changed from one negotiation to another which reduces the value of the historical data.

The main contributions of this thesis can be summarized as follows.

- ***Propose an extended negotiation model that emphasizes the notion of negotiation objects and allows for describing a variety of negotiation scenarios.***

  The proposed negotiation model is general and can be used to describe a wide range of possible negotiation scenarios. It emphasizes the notion of a negotiation object that allows for describing complex negotiation scenarios that involve multiple objects, multiple negotiation issues and multiple providers for each object.

- ***Analyze the possible negotiation scenarios in the one-to-many negotiation and define a set of scenarios that requires coordination, these scenarios are named coordination scenarios.***

  Considering the three main negotiation cornerstones, the negotiation objects, the negotiation issues per object and the number of providers per object, most of the negotiation interaction types can be classified accordingly. A subset of the possible negotiation scenarios is identified and named *coordination scenarios*. The identified coordination scenarios are the one-to-many negotiation types. This work mainly investigates the coordination problem in the defined coordination scenarios.

- ***Propose and evaluate new mechanisms that coordinate the bidding strategy for a buyer agent dynamically during negotiation.***

  The main objectives of the mechanisms are to achieve effective and robust results in terms of the utility rates and the agreement rates. In the case of multiple issues, the proposed mechanisms aim at improving the Nash product rates as well. Coordinating the bidding strategy comes as a response to the behaviors of the opponents that exist in the current negotiation. The work involves the investigation of five coordination scenarios.

  For each scenario, one or more coordination mechanisms that manage the bidding strategy (negotiation strategy) dynamically during negotiation are proposed and validated. The solution to the coordination problem depends on the idea of managing one or more negotiation strategy components during negotiation. The convexity of a concession curve, the local reservation values and the types of negotiation tactics are chosen for adaptation during negotiation. Most of the works presented in this thesis focus on developing and validating the coordination mechanisms.

- ***Propose a new Iterative Offer Generation (IOG) bidding strategy that is competitive and cooperative at the same time.***

  The *IOG* mechanism involves two offer generation tactics: IOG-trade-off tactic and IOG-concession tactic. Both tactics are used to generate counteroffers for the proposed meta-strategy. The IOG-trade-off tactic proposes different counteroffers that have the same utility in every negotiation round. Once the utility level is changed, the new counteroffers are generated according to the new utility. The IOG-concession tactic concedes in every negotiation round according to a predefined amount. The difference between the proposed IOG-concession tactic and other types of concession tactics is the that the IOG-concession tactic considers that agents can have divergent preferences over issues. Therefore it concedes more on the issues that are believed to be of high importance to the opponent.

1.5 Thesis Outline

This thesis is structured into eight chapters as follows.

Chapter 2 is the background and related work part. It introduces the basic concepts in automated negotiation and coordination and presents the related work. The chapter first introduces briefly the multiagent systems paradigm, then it moves to introduce the automated negotiation and approaches to automated negotiations including game theory, learning and reasoning, and heuristic-based approaches. The argumentation-based negotiation is also introduced briefly. Next, the dependencies and coordination is discussed including possible sources of dependencies in the negotiation context. Finally, the related work in the one-to-many negotiation is presented.

Chapter 3 presents a novel negotiation model that captures various negotiation scenarios. The model emphasizes that the negotiation object is one of the main components that are necessary for describing any negotiation scenario. The model introduces the term of delegate for describing an agents' component that can negotiate with other agents on the behalf of the agent. The utility functions that are used to evaluate offers are also presented. Finally, since an object can have one or more negotiation issues, an agent needs to decide when to accept an offer, the offers' evaluation decisions are discussed.

Chapter 4 is the coordinated negotiation and solution approach chapter. It presents the coordination problem in the one-to-many negotiation and the solution approach. In addition, it classifies the possible negotiation scenarios and defines a subset called the coordination scenario set which is the study target of this thesis. In addition, the difference between the global reservation value and the local reservation values is presented. Finally, the general experimental settings and the simulation environment is introduced.

Chapter 5 presents coordination approaches for two coordination scenarios. The first scenario is when a buyer agent is negotiating with multiple seller agents over one object that contains a single negotiation issue. The coordination approach for this scenario is based on managing the convexity of the concession curve during negotiation. The second scenario is similar to the first one except that the number of negotiation objects are more than one distinct object. One coordination approach considers the behaviors of all seller agents across all objects (global approach) and a second one considers the behaviors of the seller agents of each object alone, hence it is called the local approach. The first approach is based on managing the local reservation values whereas the second one is based on adapting the convexity of the concession curve. The combination of both approaches is called a hybrid approach. In addition, the chapter presents an empirical analysis for the different measures that can be used to analyze the behaviors of the opponents. The results of the experimental work are presented and discussed.

Chapter 6 tackles the coordination scenario when a buyer agent seeks to procure a single object characterized by multiple issues. The buyer agent negotiates with multiple providers concurrently for the sake of reaching one agreement. A meta-negotiation strategy is proposed to manage the multiple concurrent negotiations initiated by a buyer agent. The coordination approach introduces a mechanism that selects a certain tactic to use according to the current cooperation level of the opponents. In addition, a novel offer generation mechanism is proposed, the iterative offer generation (*IOG*) mechanism to generate counteroffers. It includes both a IOG-trade-off tactic and a IOG-concession tactic. The mechanism assumes that agents have divergent preferences over issues. Both tactics are cooperative and competitive. They are competitive because they aim to maximize the utility gain of the proposing agents and cooperate since they consider the preferences of the opponents when proposing counteroffers. The experimental results are presented and analyzed.

Chapter 7 investigates the coordination scenario where a buyer agent seeks to procure multiple objects given that each object is characterized by multiple issues and has a single provider. The scenario describes a monopolistic market where each service or product has one provider. The proposed coordination approach considers manipulating the local reservation values for the common issues. In addition, a global coordination mechanism is proposed for the coordination scenario where each object has multiple issues and the buyer agent is in a non-monopolistic market where each object has multiple providers. The empirical results for the coordination mechanisms are presented and discussed.

Chapter 8 is the conclusions chapter. It concludes the thesis, answers the research questions and discusses the thesis extensions and future work.

Chapter 2

Background and Related Work

After a brief introduction to the multiagent systems, the automated negotiation is introduced and its application domains are highlighted. The approaches to negotiation is presented next. This chapter starts with the game theory based approaches followed by a discussion of the learning and reasoning methods used in negotiation. It also presents different heuristic tactics used to generate offers and counteroffers during negotiation. Finally, the argumentation based negotiation approach is discussed briefly. The next part of this chapter discusses dependencies and coordination by highlighting possible interdependencies between the subjects of negotiation. The last part discusses the relationship between coordination and negotiation. It presents short introduction on some of the multiagent system coordination mechanisms and shows how negotiation is considered as one of the possible coordination mechanisms. This part emphasizes that the aim of this thesis is to coordinate concurrent multi-bilateral negotiations. In addition, the relevant related work on the one-to-many negotiation focusing on the different mechanisms proposed in the literature to coordinate multiple concurrent negotiations is presented.

2.1 Multiagent Systems Paradigm

The widespread connectivity amongst electronic devices provided by the Internet opens the door for building large scale distributed applications and systems that span over a large number of connected machines. The *cloud computing* and the *grid computing* are amongst the most important outcomes of such complex network systems. Electronic commerce is another innovative domain for doing business. In addition, the advances in computer systems lead to new computing paradigms such as ubiquitous computing [112].

Distributed systems are characterized by the fact that different entities are connected and are able to exchange messages and information. A multiagent system is a distributed computing system consisting of interacting software agents that can be used to model and solve different real world problems such as business process management [60], fault diagnosis in power systems [94], traffic management [17], etc. Task allocation [15] [83] and resource allocation [20] are two important problems in multiagent systems that captured the attention of many researchers. The main differences between the multiagent systems and the classical distributed systems is that the multiagent systems consist of intelligent and autonomous entities called agents where the agents are self-interested entities that act to achieve its predefined goals [131] [57]. In addition, agents in multiagent systems can have different owners in terms of their design and implementation and may have even conflicting goals [159].

Multiagent systems model is suitable for: 1) uncertain, complex and dynamic environments 2) where agents are natural metaphors and used to model many environments as societies of cooperating or competing agents such as most organizations 3) distribution of data, control or expertise where centralized approaches are difficult to implement 4) to solve the problem of dealing with legacy systems by wrapping a legacy component with an agent layer [159]. An agent can represent a human, a robot or a software system. In this manuscript, a software agent refers to a software system since software agents are assumed to engage in negotiation where some agents represent buyers and other agents represent sellers.

Some complex problems, especially those characterized by some social behavior, can be modeled as multiagent systems since multiagent systems are enhanced distributed systems equipped with components that are able to reason and make autonomous decisions. Examples of such complex systems are socio-economic systems and biological systems. In the electronic commerce domain, an electronic market can be modeled as a virtual place where buyer agents, seller agents and broker agents meet and trade. In general, agents in the electronic commerce are modeled as self-interested agents. In this thesis, the following definition of a self-interested agent is assumed.

Definition 2.1. *(***Self-interested agents***)*

A self-interested agent is an agent who aims to maximize its gain from any interaction with any other agent or with the environment without having the intension to harm other agents or the environment. When there is room for a win-win outcome of an interaction, the agent is willing to cooperate.

The above definition implies that a self-interested agent is a rational agent. The following is the formal definition of a rational agent.

Definition 2.2. *(***Rational agents***)*

A strict rational agent selects an option op_i over an option op_j if the expected utility (EU) of op_i is greater than the expected utility of op_j, formally, a strict rational agent selects op_i iff $EU(op_i) > EU(op_j)$. On the other hand, a weak rational agent selects op_i over op_j iff $EU(op_i) \geq EU(op_j)$.

The rationality of agents can entail a thorny problem; there are situations where an agent does not have enough computational resources or time for enumerating all the possible options or decisions, which means that agents are *rationally bounded*. In such situations, an agent aims to find a *good* or *satisficing* rather than an *optimal* solution. The bounded rationality was first discussed in [140] in the context of a human decision maker. To overcome this problem, heuristic decision making methods were proposed [141]. Heuristic methods will be discussed later.

The above definitions are consistent with the characteristics of a self-interested agent considered in the game theoretic models. From the definition above, the self-interested agent is not necessary a bad agent since it does not have the intension to harm other agents and it is willing to cooperate in case of existing a win-win situation. In addition, type of agents we consider in this thesis are not benevolent agents.

As mentioned earlier, using three types of agents, one can model any electronic market. Figure 2.1 shows two types of agent-based electronic markets, Figure 2.1(a) shows that the seller agents and the buyer agents are interacting through a broker agent while Figure 2.1(b) shows that the seller agents and buyers agents are interacting directly with each other.

The work in this thesis investigates the situation shown in Figure 2.1(b) where agents

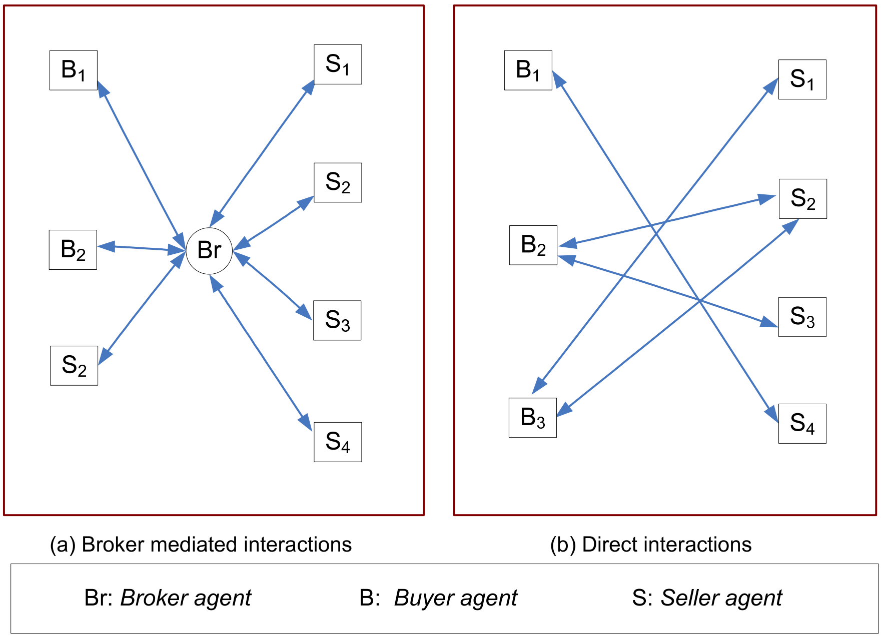


Figure 2.1: *Agent-based electronic market structures*

interact amongst each other without a broker agent. The reason is that, in reality, there would be trust problems if a broker agent or a mediator agent is introduced. In addition, an extra overhead in terms of the communication cost will be experienced in case of adopting a mediator-market model. However, Figure 2.1(b) includes three forms of interactions: one-to-one, one-to-many and many-to-many, see Section 2.2. As mentioned previously, this thesis addresses the coordination problem of an agent interacting concurrently with multiple other agents through negotiation in terms of managing the bidding strategy for the agent on the one-side dynamically during negotiation.

2.2 Automated Negotiation

Negotiation is proven to be an effective conflict resolution method and has been used extensively throughout history to settle conflicts between nations, groups and individuals [117]. Negotiation is a challenging research field in many disciplines including economics [124][145], political sciences [42], law [156], psychology and sociology [27][113], anthropology [50] and applied mathematics [51].

Scholars from the Harvard Negotiation Project have proposed a method called *princi-*

pled negotiation or negotiation on the merits [43]. The principled negotiation focuses on four points that define a negotiation method that can be used in many situations. The points are: *people, interests, options* and *criteria*. The first point emphasizes the separation of people from the problem. In many cases negotiators deviate from the main problem into personal disputes which will not help in solving the original negotiation problem. The interests point means that the focus of negotiation should be on the interest, not positions. For example, if two people are arguing against opening or closing a window, we need not to think about closing or opening the window, we rather need to think about the interests of each individual from having the window opened or closed to find a reconciled solution. The options point focuses on generating a variety of possibilities before deciding on what to do. It means that negotiators should explore many options that may include adding more negotiation issues to the negotiation problem and not leaving money on the table, i.e., reach a Pareto-optimal solution. A solution is *Pareto-optimal if and only if no agent can increase its utility without affecting negatively the utility of other agent*. The criteria point means that the result of negotiation should be based on some objective standard. The agreement needs to be based on fairness that meets certain standards, if known, such as market value or scientific merits. For more details about the principled negotiation, see [43].

The reason behind introducing the principled negotiation here is that automated negotiation using agents meet most of the principled negotiation points. For example, agents have no personal view of the problem and the separation of people from the problem is achieved. Agents are able to negotiate over interests not positions. In multi-issue negotiation, agents can have many options that make them indifferent. In addition, the principle of a win-win outcome is related to the third point, i.e., the options point. Many negotiation techniques aim to achieve a win-win agreement. Moreover, many automated techniques are designed to achieve a fair outcome (e.g., [31] [79]) which is related to the criteria point.

The interest in the automated negotiation accompanied the recent advances in computer network systems and communication technologies that facilitate the interaction between software systems. For more than a decade, automated negotiation received tremendous attention from researchers (e.g., [71] [164][30][33][68][37][40]). The work on automating the negotiation process results from the fact that computer systems are becoming more intelligent, more connected and the delegation in decision making are increasingly being granted to computer systems. Consequently, computer systems are becoming more autonomous and they need to interact to cooperate and coordinate their actions to achieve their goals. Negotiation is one of the most effective methods for managing the inter-agent dependencies at run time [58]. Automating the negotiation process can help negotiate complex contracts [68]. According to Sandholm, the automation of negotiation [127]:

> *can save labor time of human negotiators, but in addition, other savings are possible because computational agents can be more effective at finding beneficial short-term contracts than humans are in strategically and combinatorially complex settings.*

Improving the results of negotiation in terms of utility rate and/or agreement rate is another advantage. In addition, negotiation may improve the social welfare of the agency [36].

Automated negotiation borrows from other disciplines such as Game Theory, Economics, Artificial Intelligence and Psychology. However, the related literature suggests that three areas related to automated negotiation are of most importance [61] [80]:

- **Negotiation Protocols:** rules of encounter. This covers the participants (e.g., buyers and sellers) in the negotiation process, the permissible messages (e.g., sending a bid) amongst the participants, the negotiation states (e.g., negotiation is active) and the events that cause the change in a negotiation state, e.g., bid accepted.

- **Negotiation Objects:** a negotiation object can be characterized by a single issue such price or more, e.g., price, quality, delivery time etc which is called the object structure. An agreement entails agreement over the issues of an object. The negotiation protocol determines the type of operation that can be done on an agreement including the structure and the content of the agreement. There are three possible operations that can be done to the agreement structure (set of negotiation issues) and its content during negotiation: 1) both are fixed and the opponents(s) can take (accept) or leave (reject) the offer 2) opponents can propose counteroffers with different issue values from the received ones 3) opponents can change the structure of the agreement by adding or removing issues during negotiation which is sometimes called *issue-manipulation* [33].

- **Decision Making Models:** the set of algorithms or methods an agent uses to determine its next offer or counteroffer, i.e., the bidding strategy. The decision making models can be game theoretic based models, heuristic based models or argumentation-based approaches. The decision making models must be aligned with the negotiation protocol and is affected by the operation allowed on the agreement structure and its contents. In addition to the adopted negotiation protocol, the set of issues and their types (i.e., an issue can take continuous of discrete values) affect the range of a possible decision and the intricacy of the decision making models [33].

In some auction models (e.g., English auction, Vickrey), the protocol allows buyer agents only to bid on an issue and the room for employing different decision models is limited since the dominant strategy for a buyer agent is to bid up to its *reservation value*. The reservation is defined as *the minimum/maximum acceptable value of an issue*. It is minimum when an agent (e.g., a seller agent) is in a position to gain a resource such as money and maximum when an agent (e.g., a buyer agent) is in a position to lose a resource such as money too.

In cases where a protocol does not describe an optimal strategy for an agent (e.g., the alternating offer protocol), the decision making models and mechanisms receive the main attention. This is the case where agents can bargain to reach an agreement. Assuming fixed values for the agreement structure does not allow for bidding, bargaining or strategic conduct. In summary, the settings of any of the above factors can affect the possible set of negotiation outcomes.

Given the assumption that agents can bargain by exchanging offers and counteroffers, negotiation can be classified into two types [67]:

1. **Distributive negotiation**: This type of negotiation assumes that a gain for one agent is a loss for another. It is described as *zero-sum* game in the game theory terminology. This type is also called positional bargaining. Distributive negotiation exists if the negotiating agents have the same preference profile on the negotiation object structure. For example, if the negotiation object contains the

price issue then a gain for one agent during negotiation means a loss for one or more other opponents.

2. **Integrative negotiation**: This type of negotiation exists when agents negotiate over multiple negotiation issues given that agents have divergent preferences over some or all issues. In case of integrative negotiation, agents have a chance to reach a *win-win* agreement. This kind of win-win agreement can happen because an agent may concede on an issue that is less important to him and more important to its opponent(s) and vice versa.

The type of negotiation affects the decision making mechanism used by agents during negotiation. Both of the above types are considered in this thesis. When the negotiation is distributive (mainly when agents are negotiating over an object containing a single issue), the decision making mechanisms are purely competitive while the decision mechanisms can be competitive and cooperative at the same time in case of integrative negotiation.

Automated negotiation has the potential of leading to a giant step forward in many application domains. The main application candidate domains are: *electronic commerce* (e.g., [101][103]), *supply chain management* (e.g., [120][157]), *task scheduling and allocation* (e.g., [166][65]) and *resource allocation for grid and cloud systems* (e.g., [138][2]). Another potential application domain where automated negotiation can play an important role is the dynamic load management of the power grid that allows for both, cost-effective use of electricity production capabilities and customer satisfaction [9]. Brazier et al. propose a component-based multi-agent system that manages electricity load using negotiation [9]. Three application scenarios are presented and discussed in Section 1.2.

In the *service oriented* domain, agents usually negotiate to establish the service level agreements (*SALs*) over the quality of service (*QoS*) under negotiation (e.g., [134][162]). *QoS* is the non-functional characteristic of a service (e.g., reliability) which distinguishes between functionally equivalent services. It is the focus of competition between providers of functionally similar services. A competitive criterion in the service oriented domain is the flexibility in the number of possible *QoS* options that is available for customers to choose from. The current offer-based methods of *QoS* show either little or no flexibility in the possible number of available options for the combinations of the *QoS* configurations. The service configuration flexibility problem stems from the fact that in many cases, the number of possible combinations of different attribute values of services is large. When a service is characterized by several issues, then automated negotiation can be a flexible solution for establishing the *SLA* between a customer and a provider.

The reason is that the provider does not need to enumerate varying service characteristics by recounting the possible number of values that can be assigned to different attributes of each negotiation object. In theory, when the issues are of a continuous type, the number of possible *SALs* is infinite. Negotiation can be considered as a search mechanism where agents jointly search the *SLAs* space for a possible agreement over a certain *SLA*.

Web services composition is an important application domain where automated negotiation can play an important role in the process of procuring different services. Besides that an agent can search for a certain service provider(s), an agent can negotiate on the behalf of its owner over the nonfunctional characteristics of a web service such as response time, throughput, reliability, etc. Using agent technologies to conduct the process of provisioning web services can be more efficient than using manual methods that consume time, effort and cost more. For example, a coordinated-negotiation architecture is proposed [21] for web-service composition to ensure end-to-end *QoS*. In addition, the results of manual procuring of web services can be less efficient in terms of procuring the most suitable web services in terms of quality of service.

In multiagent systems, there are three forms of interactions determined by the number of interacting partners and their respective positions. The basic form is the *bilateral interaction* where two opponent agents interact. For example, B_1 and S_4 agents in Figure 2.1(b) conduct bilateral interaction. The second form is the *one-to-many* interaction where an agent interacts with multiple agents. In Figure 2.1(b), agent B_2 interacts with agents S_2 and S_3. The last form is the *many-to-many* interaction where multiple agents interact with multiple other agents. Different market mechanisms can be represented by one of these interaction forms. For example, the English auction can be modeled as the one-to-many form where many buyers interact with one seller. The reverse English auction can also be represented by the one-to-many form where many sellers interact with one buyer. The double continuous auction can be represented by the many-to-many form. The interaction between agents can be either a *one-way* model or a *two-way* model. The one-way interaction model refers to auctions while the two-way interaction model refers to negotiation where agents exchange offers and counteroffers.

One of the first explicit architectures for the one-to-many negotiation was presented in [115] where the buyer agent consists of sub-negotiators and a coordinator. The sub-negotiators negotiate concurrently with a set of seller agents given that each sub-negotiator negotiates with one seller. As mentioned earlier, this thesis investigates mainly the situation of a buyer agent negotiating concurrently with seller agents for the purpose of reaching one or more agreements over one or more negotiation objects. During the last decade, work has been done to address the one-to-many negotiation as an alternative mechanism to the single-sided auction [106] [48] [105] [161] [3] [2].

Adopting the one-to-many negotiation as an alternative to the single-sided auction has many advantages. Not only does the agent on the one side receive offers, but it also proposes counteroffers to each individual agent on the $many$ side. Accordingly, the chance of reaching an agreement will improve since each agent in the negotiation process analyzes the previous offers in the current negotiation encounter which aims at predicting the preference structure of its opponents and proposes counteroffers that might improve the chance of reaching an agreement.

To shed more light on the advantages of adopting concurrent negotiation over the single-sided auction, the following few points provide more information [105]:

- when agents seek agreement over multiple attributes or issues, a buyer can select an offer from a set of offers proposed by the seller agents in case of a reverse auction and a seller can select an offer from a set of offers offered by the buyers in a forward auction. In both cases, the buyer in the first case and the seller in the second case do not have the chance to ask for modification of any of the proposed offers. In the multi-bilateral concurrent negotiation, an agent has the chance to respond and ask for a specific value for each issue. This is important since buyers and sellers can have divergent preferences over different issues. For example, a buyer is willing to offer a premium price for having an item delivered within 24 hours while other buyers can wait one week for the same item to be delivered for paying a lower price. In other words, the chance of reaching an agreement will improve since the agent on the ‘one’ side in the negotiation process may analyze the previously received offers in the current negotiation encounter which aims at predicting the preferences of its opponents and tries to propose counteroffers that might improve the chance of reaching an agreement. It is obvious that the multi-bilateral concurrent negotiation improves the search for agreement(s) process since the approach allows buyers and sellers to search for offers that meet their criteria more efficiently.

- when a buyer agent receives multiple offers from different sellers, its bargaining power will improve and its negotiation strategy can be different against each seller. For example, some sellers might be desperate for reaching a deal and that fact can be used by the buyer to secure a good deal.

- the agreement reached in a certain negotiation encounter can affect (help) other negotiations. For example, a buyer can not accept a worse deal than an existing one.

- the time for reaching an agreement can be reduced in comparison with time needed by auctions since some auctions need to wait for a certain time before announcing any agreement. In the concurrent negotiation approach, a buyer can accept an offer at anytime and finish negotiation before the deadline.

The downside of using the multi-bilateral concurrent negotiation approach instead of auction models is the communication cost and the need for coordination mechanisms to manage the negotiation strategies of agents.

2.3 Approaches to Negotiation

The negotiation objective criteria vary. In competitive environments, each agent aims to maximize its gain regardless of the gain of other agents. In other situations, agents seek to maximize both, the individual gain the system gain. As the bidding strategy is a critical part in the negotiation process since it is the process by which an agent decides on the value and the content of the offer/counteroffer for the next negotiation round, the focus in most negotiation literature is on devising bidding strategy techniques that can achieve an optimal solution to the negotiation problem. Given the fact that automation of the bidding process is complex, it is difficult to find an optimal strategy for a dynamic process such as negotiation [82], various negotiation approaches are proposed in the literature to automate the negotiation process, e.g., [33]. There are three main negotiation approaches: *game theory-based*, *argumentation-based* and *AI-based* approaches. The following sections discuss each briefly.

2.3.1 Game Theory-Based Approaches

In many cases, the negotiation problem is treated as a *bargaining problem* which is defined by Rubinstein as [125]:

> *Two individuals have before them several possible contractual agreements. Both have interests in reaching agreement but their interest are not entirely identical. What "will be" the agreed contract, assuming that both parties behave rationally?*

Game theory is a mathematical tool that can be used to answer that bargaining question under certain assumptions. Game-theory is a branch of economics that is used to study and analyze how self-interested agents make decisions during their interactions [109]. In their book titled '*The Theory of Games and Economic Behaviour*' [154], John von Neumann and Oskar Morgenstern invented the mathematical theory of games in 1944. The proposed mathematical framework was limited since it is applicable only under some strict conditions. Since then, the framework has gone under many iterations of refinements to make it work under less strict conditions [123]. In the context of game-theory, an agent can be defined as an entity with preferences that aims to maximize its utility which is measured by a *utility function* [123]. The utility function of an agent assigns a value (usually numeric) to the outcomes of the game.

Optimal strategy and *equilibrium* are two important keywords in game theory since researches aim to find the optimum strategies for interacting agents that lead to equilibrium considering their preference and possible alternatives. The most famous type of equilibrium is *Nash equilibrium*. Two strategies st_1 and st_2 are said to be in Nash equilibrium if an agent is playing st_1 and its opponent agent can do no better than play st_2 and vice versa.

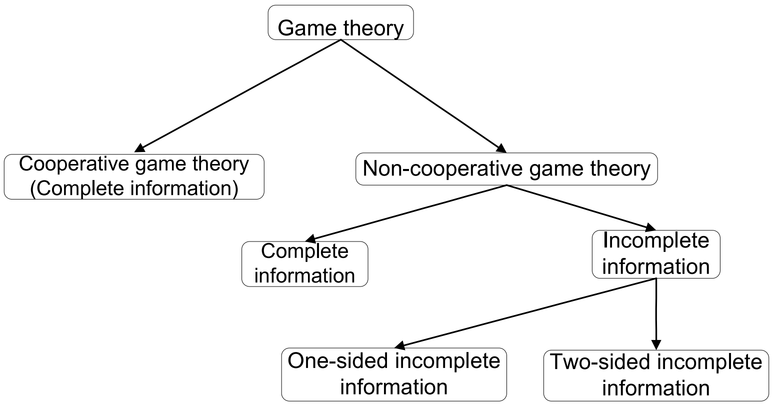


Figure 2.2: *Taxonomy of game theory*

Negotiation is a bargaining problem where two or more agents have conflict of interest over an issue or more and there is a possibility for achieving a mutually beneficial agreement(s) and the agreement(s) needs approval from all parties. Bargaining theory is a part of game theory that investigates and analyzes bargaining games. Game theory can be divided into *cooperative* and *non-cooperative* game theory. A possible taxonomy of game theory is shown in Figure 2.2 [77]. The cooperative game theory aims at finding a solution while given a set of possible outcomes rather than on the specific rules of the game or the negotiation process. The chosen solution usually needs to satisfy some conditions such as being fair or stable. These conditions or properties are called axioms. For example, if the condition is that the two bargainers gain the same utility upon an agreement, then this would be an axion [77] [47].

The eminent work of Nash results in defining a unique solution satisfies four properties which are called *Nash axioms* [102]. Assuming that players are rational, the axioms are: 1) *The outcome is invariance to equivalent payoff representation*. This means that the outcome of the bargaining process is not affected by a utility function transformation and keeps the same ordering over preferences 2) *Pareto optimality*. There is no other agreement that can make both players better off or make one player better off without making the other player worse off. 3) *Independence of irrelevant alternatives*. This means that the outcome is not related to irrelevant outcomes, i.e., if the current agreement is feasible, other alternative agreements are not considered 4) *Symmetry*. If the players are indistinguishable, they should gain the same utility, i.e., no discrimination in selecting the agreement.

When the previous assumptions hold, Nash proves that there is a unique solution (*Nash-bargaining solution*) that maximizes $((u_1(x_1) - d_1).(u_2(x_2) - d_2))$ which is called *Nash-product*. The $u_1(x_1)$, $u_2(x_2)$ are the pay-offs of the solutions x_1 and x_2 respectively. In addition, d_1, d_2 are the payoffs in case of conflict outcome.

Kalai and Smorodinski argue against Nash's third axiom and suggest a new axiomatic solution called *kalai-Smorodinski bargaining* solution by replacing the third axiom of Nash by the *monotonicity* property, see [63]. Since the outcome of the negotiation process that is considered in this thesis depends on the interactions amongst agents, the approach of cooperate game theory is not applicable here.

On the other hand, if a game has a well defined set of rules defined by a certain protocol that is known by the players before the start of the game, then the *non-cooperative* game theory is the branch that handles such situations. The actions of each player at each step during the game are determined by a bargaining strategy given the historical information of negotiation. The objective of the non-cooperative game theory is to find the equilibrium strategy to define the rational behaviors of players, then the rational behaviors of all players decide the outcome of the game. As mentioned before, Nash equilibrium is an example of such an equilibrium. For example, a strategy equilibrium for a buyer agent and a seller agent who have unlimited negotiation time is that each agent offers the minimum allowed concession in each negotiation round until their offers match. There is no benefit for any player to deviate from this strategy by conceding, for example, more than the minimum allowed concession. As Figure 2.2 shows, the non-cooperative game theory is divided into *complete information* and *incomplete information*. In the complete information case, agents know about the preferences of each other. Different protocols lead to different outcomes at the subgame perfect equilibria (*SPE*) [77]. Games such as *ultimatum* [99], *alternating offers* [125] and *monotonic concessions* [122] were analyzed and investigated to find the *SPE*.

The *mechanism design* and *sequential bargaining* are two approaches usually used to study the non-cooperative game theory with incomplete information. The mechanism design abstracts the process of bargaining and uses the players' private information to find the bargaining solution [77].

In sequential bargaining games, the outcome is reached by exchanging offers and counteroffers between the players. The sequential bargaining games are divided into *one-sided incomplete information* and *two-sided incomplete information*, see Figure 2.2.

Assume that a buyer and a seller would like to reach an agreement over a certain issue using the alternating offer protocol (i.e., by exchanging offers and counteroffers) and if one player (say the buyer) knows about the reservation price value of the seller, then the game is called a one-sided incomplete information game. If both, the seller and the buyer do not know anything about each other (e.g., reservation values) then the game is called a two-sided incomplete information. When analyzing the two-sided incomplete information games, researchers assume that each player has a limited number (e.g., 2) of types to simplify the analysis, see [16].

Finally, using game theory, it is possible mathematically to analyze games in terms of finding the equilibrium fulfilling strategies. However, to do that, game theory applies strict conditions. It assumes that agents have the ability to assign '*utility values*' for all possible outcomes. In many cases, a utility function that maps an outcome to a numeric value does not exist. For humans, it is difficult even to rank different outcomes especially when negotiating over objects characterized by multiple issues. Another limitation is that game theory generates specialized models that are applicable in certain types of interdependent decision-making and fails in producing a general model. In addition, game theory assumes that players or agents are rationally unbounded which means that they know all possible solutions within a feasible range of outcomes or can find them within an acceptable computational time. Finally, players are assumed to have full knowledge about the environment and about the opponents in terms of their preferences over different outcomes. The assumption about total rationality and full knowledge are unrealistic since agents are computationally bounded and rarely know the outcome preferences of their opponents. Game theory is suitable in terms of analysis and can be used in automated negotiation when the relevant conditions are assumed to exist, see [77] [47] [58].

To enable adopting automated negotiation in more realistic situations, the artificial intelligence (*AI*) techniques are used in automated negotiation to relax the strict assumptions of game theory. The *AI* techniques use learning and reasoning methods that can help agents in learning and reasoning about their opponents' models and adapt their behavior to the current situation. The next section discusses briefly some of the *AI* techniques that are relevant to automated negotiation.

2.3.2 Learning and Reasoning Based Approaches

In general, it is difficult to apply game theory in real life negotiation situations due to its strict assumptions. The artificial intelligence (*AI*) approaches are applied in the field of automated negotiation to relax these assumptions. The learning and reasoning methods of *AI* are proposed to deal with the situation of incomplete information and limited computational resources. In the automated negotiation context, an agent aims to learn about the model of its opponent. A negotiating agent aims to model its opponent in terms of learning or approximating one or all of the following:

- preference profile, such as reservation value, deadline, preferences over issues, preferences over the outcomes etc.
- negotiation tactics and their associated parameters. For example, an agent can aim on finding its opponent's offer generation technique, e.g., time-dependent.

The subfields of artificial intelligence that are relevant to automated negotiation is *learning and reasoning*. To facilitate concise summary of the work done in automated negotiation using learning and reasoning methods in *AI* and partially based on [126], Figure 2.3 shows a simple classification of the *AI* learning and reasoning methods that are relevant to automated negotiation. The classification shown in Figure 2.3 is neither comprehensive nor precise. Figure 2.3 does not include all the *AI* techniques that are relevant to automated negotiation. In addition, one can argue against the classification itself since some *AI* methods can be classified under more than one category.

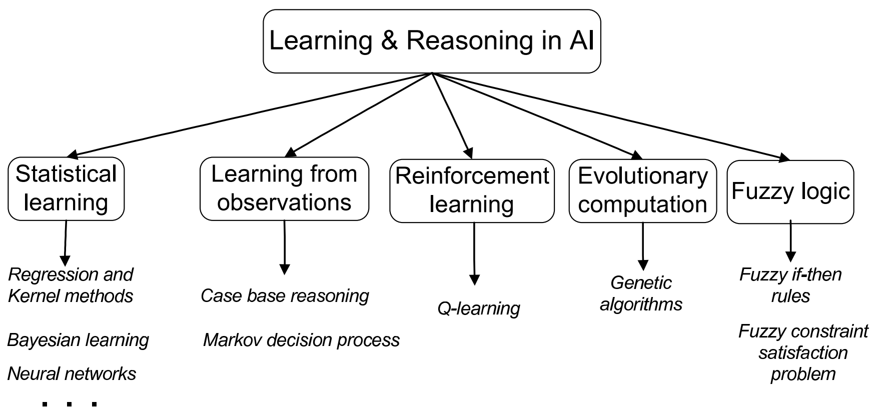


Figure 2.3: *AI Learning & reasoning methods used in automated negotiation*

If an agent can model its opponent, it can use relevant decisions to maximize its utility gain or achieve other negotiation objective criteria. The most used learning methods are classified under statistical learning where agents apply statistical techniques to predict and/or to learn information about their opponents. Learning can be offline, online or both. The offline learning uses previous information (e.g., outcomes of previous negotiation encounters) in the learning process while the online learning uses the information available during the current negotiation encounter. In most cases, the dynamic information that are available to the agents in the current negotiation encounter are the current negotiation threads, see Section 3.2. Domain knowledge is another source of information. In addition, a probability distribution over unknown parameters (e.g., deadline) is a useful source of information for agents. Finally, some approaches assume a predefined set of models about the opponent.

Regression methods are used in negotiation to estimate the parameter(s) of a given negotiation decision function using the thread of the current negotiation encounter. Regression methods are also used to predict the type of negotiation tactic (e.g., time-dependent) used by the opponent assuming that the opponent uses a predefined set of tactics [11] [12]. In one-to-many negotiation, [135] uses linear regression to predict the future proposals of an opponent. The prediction result is used to decide whether an agent should continue negotiating or accept the best offer in an acceptable list and quit negotiation. The coordination process involves deciding on proceeding or terminating the concurrent negotiation. The work in [135] assumes that agents are negotiating over a single issue.

A limitation of the regression methods is the assumption about the decision models of the opponent. In addition, the online prediction using regression methods can be computationally expensive.

On the other hand, Coehoorn and Jennings use the *kernel density estimation KDE* method to approximate the preferences of an opponent over various issues in multi-issue negotiation [22]. The *KDE* is a non-parametric statistical method that can be used to estimate the probability density function of a stochastic variable. The authors use the difference between the last two offers of the opponent to find a relation between this difference and the preference in terms of weight the opponent has for each issue. Once an agent approximates the weight that its opponent places on each issue, it uses the trade-off method to generate its offer aiming to reach a win-win agreement. The limitation of this approach is that the agent using the *KDE* method needs a probability density function over the opponent's likely weights for the various issues estimated from previous negotiation encounters, i.e, the history of previous offers and counteroffers. In addition, the authors assume that the agent uses time-dependent tactics in order to behave differently overtime.

In sequential decision-making models (e.g., alternating offers protocol model) where there are sequence and dependent decision making points and the decision maker is able to update its beliefs after making a certain decision and receiving feedback, *Bayesian learning* would be a suitable learning model [164]. Zeng and Sycara propose "modeling beliefs about the negotiation environment and the participating agents under a probabilistic framework using a Bayesian learning representation and updating mechanism [164]". We use a similar example to the one presented in [164] to briefly explain how the Bayesian learning works. Consider a buyer agent negotiating with a seller agent over a price issue using Bayesian learning. In this case, the buyer agent needs to have a partial belief about the reservation price (RV_{seller}) of the seller represented as a probability distribution over the expected reservation prices. This belief can be modeled as a set of hypothesis $H = \{H_i | i = 1, 2, ...n\}$. Say that, for H_1, $RV_{seller} = 120$ and for H_2, $RV_{seller} = 150$. Each hypothesis is true to a certain extent. The priori knowledge about each hypothesis is represented as a probability distribution. The updating process in Bayesian learning starts when new information is received, see Equation 2.3.2.

$$P(H_i|e) = \frac{P(H_i)P(e|H_i)}{\sum_{j=1}^{n} P(e|H_j)P(H_j)} , \tag{2.1}$$

where $P(H_i|e)$ is the posterior knowledge or estimation of the RV_{seller} and $P(e|H_i)$ is an encoded domain knowledge about the probability of event e given H_i. To run a numerical example, assume that the buyer agent has no more information about the H_1 and H_2 which means that $P(H_1) = 0.5$ and $P(H_2) = 0.5$. Regarding the domain knowledge, it can be known that sellers usually add 15% to their reservation price. The encoded domain knowledge is $P(e|H_1) = 0.35$ and $P(e|H_2) = 0.1$ where e is the event that the seller asks $120 + 0.15 * 120 = 135$. Assume that the seller agent offers \$135 then the posterior priorities are:

$$P(H_1|e) = \frac{0.5 * 0.35}{0.35 * 0.5 + 0.1 * 0.5} = 77.78\%$$

$$P(H_2|e) = \frac{0.5 * 0.1}{0.35 * 0.5 + 0.1 * 0.5} = 22.22\%$$

The buyer agent updates its knowledge about the reservation value of the seller accordingly. For more information, see [163][164].

Bayesian learning is used to learn both the issue preferences and the issue priorities of an opponent in multi-issue negotiation [53]. One of the proposed model assumptions is that an agent has some knowledge about issue priorities of the opponent. Another assumption is that a hypothesis space of predefined function types about the opponent is assumed.

The Bayesian learning assumes some knowledge to work such as the encoded specific domain knowledge which is not always available. In addition, the Bayesian framework does not provide a negotiation strategy in the form of concession behavior. Applying the Bayesian learning in one-to-many negotiation is more difficult since an agent needs to have some information about a large number of agents which is difficult to do in reality given that agents negotiate in an open and dynamic system.

Neural networks do not assume any relationship between the input and out variables since this kind of relationship will be learned by the neural network itself. A neural network needs a training on a training dataset when using offline learning, or it can start processing information after a certain number of offers are exchanged between agents. For example, [13] uses both, offline and online neural network training to model the negotiation process in a time-series style. The neural network used in [108] was trained offline and then online before testing it. The trained neural network is used by a seller agent negotiating with a buyer agent over the price issue. Using the neural network, the seller agent needs to predict the next price proposal of the buyer agent given that the buyer agent has already sent three proposals. The experimental results show that the seller agent using neural network achieves more deals when compared with a seller agent using Q-learning when the deadlines are long.

The drawback of using neural networks is that they need training before they can perform well. In addition, if an agent using a neural network is negotiating with an opponent agent playing different strategies from the ones that were used in the training set, the neural network could have unpredictable behavior.

The idea of *Case-based reasoning (CBR)* is to solve a new problem using or adapting previously found solution(s) used to solve similar problems. The *CBR* mechanism elicits information and learns from previous cases histories, hence it does not need explicit information about some domain knowledge [155]. In negotiation, an agent adopting *CBR*, uses previously stored cases for comparison and decision making during negotiation encounters. The cases that are kept in the case database and used later are the ones who achieved successful outcomes in negotiation. Sycara was one of the first to use *CBR* in the PERSUADER program, that resolves labor disputes using negotiation where "contracts, impasses and arguments are used as basis for Case-Based Reasoning at performing" the required tasks [148]. Argumentation and *CBR* are used in [167] to manage the negotiation strategy in e-commerce. Matos and Sierra use *CBR* as a technique to assign parameter values to negotiation tactics and determine the weights that will be used to combine those tactics [93] whereas the fuzzy rules are used to adapt the chosen solution considering the environmental information before making new offers.

A possibilistic case-based reasoning is used in [10] to predict negotiation outcomes for a potential set of negotiation partners. The partner with the highest score or rate is selected to be a negotiation partner. However, this approach was not used in the process of managing the negotiation strategy during negotiation.

One of the drawbacks of using *CBR* in negotiation is that an agent requires a large number of previously stored cases in order to achieve good results since agents in many cases, exist in open and dynamic environments. In addition, a *CBR* agent may not be able to reason during negotiation when it faces a situation where its opponent behaves differently from any stored case.

The *Markov decision process (MDP)* is a stochastic process that has been used to model the negotiation process, e.g., [101][149]. Narayanan and Jennings model a bilateral negotiation as two non-stationary *MDPs* because each agent views the state space differently, and they are non-stationary processes due to the environmental dynamics which makes the probability of transition from one state to another vary over the negotiation time [101]. In their model, the authors assume that agents have some information about the transition function represented as probabilistic knowledge. In addition, they assume the Markov property in the system (i.e., the state transition of a system depends only on the current state) as they argue that only the current state of the system triggers the process of selecting an effective strategy. However, they state that more work needs to be done to verify that claim.

The state space in [149] is modeled as a set of negotiation tactics. An agent using the *MDP* method needs to negotiate with several other agents to build an empirical probability distribution of the tactics after which the agent updates the empirical probabilities by learning from other agents' responses. A decision making strategy based on a tractable Markov chain model of negotiation process is proposed [3] to help an agent adopting that model to make a decision on whether to accept the best received proposal from a set of partners or to keep on negotiating in case the expected utility in the next proposals will be better. The main drawback of using the *MDPs* is that it requires a meaningful probability distribution over the state transition matrix in order to deliver effective outcomes.

Reinforcement Learning (RL) is a learning method where agents learn by experience. An Agent observes the state of its environment and takes action. Depending on the action it takes, it receives either a positive or negative reward. When an agent has the opportunity to take a new action, it selects the action that brings him a positive reward. This process of learning is repetitive and the agent is expected to learn over many repetitions [146].

In negotiation, agents adapt their negotiation strategies according to the feedback received after using a particular strategy. The feedback can be an opponent's response to using a certain strategy. For example, after using a certain strategy, the opponent may accept, reject or quit negotiation.

Q-learning is the most used type of reinforcement learning. An agent using Q-learning updates the Q-value when it selects an action a given a state s, see Equation 2.2. In negotiation, the Q-value is updated at every negotiation round for the chosen action a taken while in state s.

$$Q(s,a) \leftarrow Q(s,a) + \alpha[R(s') + \gamma \max_{a'} Q(s',a') - Q(s,a)] \;, \tag{2.2}$$

where $\max_{a'} Q(s',a')$ is maximum expected reward (e.g., utility) of the next state s'. The learning rate α controls the amount of Q-value update, $\alpha \in [0,1]$. If a Q-learning agent assumes $\alpha = 0$ then the agent does not learn (i.e., it does not update the Q-

value) since it keeps the old Q-value. When $\alpha = 1$, the agent considers the most recent information. The factor $\gamma \in [0, 1]$ is the discount factor. If $\gamma = 0$ then the agent considers the current rewards. If $\gamma = 1$ then the agent will look for a high reward in the future. $R(s')$ is the immediate reward after choosing the state s'.

In automated negotiation, Q-learning is used to select a negotiation strategy from a set of different combinations of negotiation tactics (e.g., [14]) where an agent learns to select an appropriate negotiation strategy during negotiation. The choice of a certain strategy can be either rewarded or punished. The Q-learning agent is expected to perform well after a certain number of iterations depending on the number of states, e.g., strategies.

The problem of using Q-learning in negotiation is that Q-learning has proven to have slow convergence towards near-optimal solutions in comparison with other techniques such as genetic algorithm based classifier systems [108]. Another problem is that, an agent using Q-learning has to reason whether to exploit the current situation or explore other possible solutions.

Evolutionary computation methods are based on models of natural selection. The three most popular forms of *evolutionary computation* are *genetic algorithms*, *evolution strategies* and *evolutionary programming*. The genetic algorithms model evolution at the level of genes. Evolution strategies model evolution at the level of individuals competing for resources while evolutionary computation models evolution at the level of species competing for resources [5].

A genetic algorithm starts with a randomly generated population. The population is evaluated using a fitness function and with a probability related to the fitness of each individual, an individual can be transferred into the next generation either unchanged, mutated or created by the crossover method where information from two parents are used to make a new individual. The process is repeated until some stop condition becomes true. In negotiation, the evolutionary computation methods allow agents to empirically learn using good negotiation strategies. A genetic algorithm based learning technique is proposed in [107] for learning negotiation strategies. The strategies are structured as sequential rules consisting of offers separated by thresholds. Each threshold represents the utility of an offer. However, the model offers little expressiveness to model strategies with even simple decision rules. Tu [150] proposes an approach based on genetic algorithms that evolves from negotiation strategies where each strategy is presented as a finite state machine. Each strategy competes against other strategies and is adapted over time depending on the completion outcomes using a genetic algorithm.

If the population size is not large, genetic algorithms can produce acceptable outcomes. However, in real world scenarios, their application is limited due to the large number of negotiation strategies. Accordingly, the population search space becomes large and intractable.

Fuzzy logic is used in negotiation as a decision making approach for selecting an appropriate negotiation strategy considering current negotiation environmental conditions, e.g., [93] [139]. When using fuzzy logic, it is important to choose a fuzzy model that suits a certain system since fuzzy modeling is the most important issue in fuzzy logic [144]. In automated negotiation, two main fuzzy logic models are used to model the decision making process: the *fuzzy if-then rules* and the *fuzzy constraint satisfaction problem*. The fuzzy rules are a set of rules applied to certain variables. When a certain fuzzy rule is satisfied, a corresponding action is initiated. For a multi-input and single-output system, the fuzzy rule looks like [144]: $R^i : if x_1\ is\ A_1^i\ and\ x_2\ is\ A_2^i \ldots and\ x_n\ is\ A_n^i,\ then\ y\ is\ B^i$, where R^i is the ith rule, x_j is the input variable and A_j^i and B^i are fuzzy variables. Matos and Sierra use fuzzy rules to adapt the current mental state of an agent by adapting the parameters of the negotiation tactics and their contribution weighs in the next offer while considering the current environmental situation. Fuzzy rules are used in [139] to manage the amount of concession during negotiation. They take into consideration the negotiation environmental conditions such as competition, deadlines, trading options, etc.

The problem of using fuzzy rules is that some knowledge and experience is needed to set up the rules. In addition, it is difficult to change the rules during negotiation which can be a problem in dynamic and open systems.

On the other hand, negotiation can be modeled as a constraint satisfaction problem [70] since an agent has constraints and preferences that need to be satisfied during the negotiation. To provide a more flexible model, negotiation is modeled as a *fuzzy constraint satisfaction problem (FCSP)*, e.g., [69][81] where the constraints are considered fuzzy and presented by membership functions. In general, an agent using *FCST* to model negotiation aims to reach an agreement that maximizes its gain, and when possible, to maximize the opponent's gain too, i.e., the agent aims to achieve a Pareto optimal solution. The Prioritized FCSP approach is used in [81] to handle situations in which an agent is not able to describe precisely its preferences over negotiation issues, when the agent's constraints are fuzzy. For example, if an agent is searching for a nearby inexpensive restaurant, then there is no precise acceptable preference over choosing a restaurant. A certain restaurant could be partially satisfied or partially violated. For more reasons on adopting the *PFCSP*, see [81]. The concept of *priority* in FCSP was introduced to handle the matter of existing issues with different importance. Exiting issues with different importance are the base of using trade-off in negotiation. For more detail on using trade-off in negotiation, see Section 2.3.3.5. Finally, the model assumes that agents exchange more information than the ones related to the values of issues, such as constraints about the product the buyer agent intends to buy which limits the applicability of the approach where only values over issues can be exchanged.

To wrap-up this section, the following are general comments about using learning and reasoning *AI* techniques in automated negotiation:

- even though *AI* techniques relax the strict conditions assumed for applying game theoretic techniques, i.e., complete knowledge and unbounded rationality, *AI* techniques still require either partial knowledge represented as probability distribution over variables (e.g., Bayesian learning) or training before the start of negotiation, e.g., neural networks
- most *AI* techniques are proposed for bilateral negotiation
- most *AI* techniques are designed for the situation where agents negotiate over one object, and in most cases that object contains the price as the only negotiation issue.

2.3.3 Heuristic-Based Tactics

Negotiation is a dynamic and non-deterministic process. The assumption is that agents work under incomplete knowledge since the preferences over the negotiation outcomes, the utility structure and the deadlines are considered private information for each agent. The heuristic-based models provide approximate solutions to the problem of the bidding strategy. The heuristic approaches can be used in different application domains and allow an agent to show different behaviors in terms of its concession strategy that help it to adapt to the current situation. The heuristic-based approaches are computationally efficient and tractable since they do not need to exhaustively search the negotiation space while looking for the optimal choice.

Widely used heuristic based techniques were proposed in [33]. The proposed techniques are called negotiation tactics and consist of a set of decision functions categorized according to some negotiation variables such as time or according to the concession behavior of the opponent. The following few sections provide an overview.

2.3.3.1 Time-Dependent Tactics

An agent uses the *time-dependent tactics* to generate its offers/counteroffers takes into consideration both, the time elapsed since the start of negotiation and the negotiation deadline. In addition, the convexity of the function curve affects the amount of generated concession. The convexity parameter used in the literature is often denoted as β. The time-dependent tactics do not take the concessions of the opponents into consideration in the process of generating offers/counteroffers. Different functions can be used to control the amount of generated concession on each issue in each negotiation round. For example, polynomial (see Equation 2.3) and exponential (see Equation 2.4) functions were proposed [33] and used in conducting various experiments that aim to evaluate empirically the proposed negotiation tactics and strategies. It is worth noting that the behavior of these functions is monotonic, i.e., each proposed offer/counteroffer will have less utility than the previously offered one. The monotonic behavior is realistic in many real life applications. For example, it would be inappropriate for a merchant to ask for a higher price than the previously asked one during the same negotiation encounter.

$$\alpha^{\mathbb{d}}_{j_l}(t) = \kappa^{\mathbb{d}}_{j_l} + (1-\kappa^{\mathbb{d}}_{j_l})(\frac{min(t, t^{\mathbb{d}}_{max})}{t^{\mathbb{d}}_{max}})^{\frac{1}{\beta}} , \tag{2.3}$$

$$\alpha^{\mathbb{d}}_{j_l}(t) = e^{(1-\dfrac{min(t, t^{\mathbb{d}}_{max})}{t^{\mathbb{d}}_{max}})^{\beta} \ln \kappa^{\mathbb{d}}_{j_l}} , \tag{2.4}$$

where $\alpha^{\mathbb{d}}_{j_l}(t)$ is the function that controls the amount of concession in the next negotiation round, k is a constant that determines the initial concession at $time = 0$ given that $k \leq \alpha^{\mathbb{d}}_{j_l}(t) \leq 1$ and $0 \leq k \leq 1$. The β parameter controls the convexity of the concession curves. With different β values, the first two functions behave in a similar way except in the extreme values of β in which the function in Equation 2.3 (called polynomial function) tends to concede more quickly with higher beta values than the function in Equation 2.4 (called exponential function), see Figure 2.4. When the values of beta are small, the exponential function waits more than the polynomial function before it starts conceding.

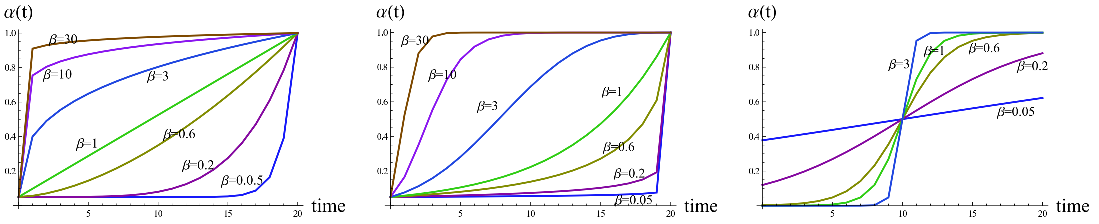


Figure 2.4: *Polynomial (left), exponential (middle) and sigmoid decision function curvatures using different* β *values*

The sigmoid function (see Equation 2.5) is another decision making mechanism that controls the amount of concession in each negotiation round [168]. Its behavior is different from the behavior of the functions in Equations 2.3 and 2.4. The sigmoid function starts conceding more after the *turning-point* which is in the middle of the deadline interval (i.e., $t^a_{max}/2$) for all high values of β. For small values of β, the behavior of the sigmoid function tends to be linear in terms of how it models concession. For relatively high β values, the sigmoid function offers little concessions while after the turning-point, it offers large concessions towards the reservation value of the negotiation issue. With small β values, the concession behavior is relatively stable before and after the turning-point, see Figure 2.4.

$$\alpha^{\mathbb{d}}_{j_l}(t) = \frac{1}{e^{-\beta(t-t_{mid})}} \tag{2.5}$$

After calculating the $\alpha^{\mathbb{d}}_{j_l}$, Equation 2.6 is used to calculate the real value for an issue j_l that is going to be offered in the next negotiation round.

$$x^{t_{n+1}}_{\mathbb{d}\to\mathbb{s}} = \begin{cases} IV^{\mathbb{d}}_{j_l} + \alpha^{\mathbb{d}}_{j_l}(t)(RV^{\mathbb{d}}_{j_l} - IV^{\mathbb{d}}_{j_l}) & \text{if } RV^{\mathbb{d}}_{j_l} > IV^{\mathbb{d}}_{j_l} \\ IV^{\mathbb{d}}_{j_l} - \alpha^{\mathbb{d}}_{j_l}(t)(IV^{\mathbb{d}}_{j_l} - RV^{\mathbb{d}}_{j_l}) & \text{if } RV^{\mathbb{d}}_{j_l} < IV^{\mathbb{d}}_{j_l} \end{cases} \tag{2.6}$$

In general, the first case in Equation 2.6 is used by a buyer agent who starts offering the least amount of resources (e.g., money) to its opponent seller agent for buying an object o_i, while the seller agent starts asking for high amounts of resources (e.g., money) in exchange for the negotiation object o_i.

The concession patterns shown by the functions in Equations 2.3 and 2.4 can be classified into three broad areas of behaviors that are controlled by the convexity parameter β. The three behavior types are:

- *Boulware*, where $\beta < 1$. The Boulware agent makes small concessions in the start of negotiation and continues until it reaches near its deadline where it offers large amounts of concessions and reaches its reservation value when it meets its deadline. This type of behavior represents an agent who is not desperate in reaching an agreement quickly. This type of agent is rather aims to reach an agreement with high utility.
- *Linear*, $\beta = 1$. The linear agent offers the same amount of concession in each negotiation round and this linear behavior is applied strictly to the polynomial decision function, see Equation 2.3. The behavior of the exponential function (Equation 2.4 is nearly linear when $\beta = 1$. The linear behavior represents an agent who balances between the time of agreement and the quality of that agreement.
- *Conceder*, where $\beta > 1$. The conceder agent offers large concessions at the beginning of negotiation then starts offering small concessions until it reaches its reservation value at the deadline. The conceder type of agent represents a situation where an agent is desperate in reaching an agreement regardless of the quality of that agreement.

2.3.3.2 Resource-Dependent Tactics

As the name implies, the resource-dependent 2.3.3.1 tactics depend on the amount of the available resources for determining the value of the offer/counteroffer in the next negotiation round. In Equation 2.7, the $resource^a(t)$ is a function that returns the amount of available resources at time t, such as the number of the negotiating agents or the number of the exchanged messages during negotiation etc. [33].

$$\alpha^{\mathbb{d}}_{h_j}(t) = \kappa^{\mathbb{d}}_{h_j} + (1 - \kappa^{\mathbb{d}}_{h_j}) e^{-resource^{\mathbb{d}}(t)} \tag{2.7}$$

When the amount of the available resources are low, then the value of the function $\alpha^{\mathbb{d}}_{h_j}(t)$ is high, which means that agent $\mathbb{d}$ needs to offer large concessions to improve the chances of reaching an agreement. On the other hand, when the available resources are high, agent $\mathbb{d}$ tends to offer small amounts of concessions. Time is a specific type of resource and it will be the resource that is investigated in this thesis since time is a critical factor for any negotiation process and the *time-dependent tactics* are a special type of *resource-dependent tactics*.

2.3.3.3 Behavior-Dependent Tactics

Behavior-dependent tactics or Tit-For-Tat (*TFT*) family is another approach for generating offers. When an agent uses a behavior-dependent tactic to generate offers, it imitates the behavior of its current opponent in terms of the opponent's concessions. The imitation procedure depends on weather the imitation takes into consideration the recent or old amount of concessions offered by the opponent. In addition, the imitation can be exact (where an agent concedes the exact amount of its opponent concession) or proportional where an agent offers an amount of concession proportional to the amount of concession offered by its opponent. To accommodate the stated imitation factors, three behavior-dependent tactics (*TFT*) are proposed [33]. The type of *TFT* shown Equation 2.8 is called *Relative Tit-For-Tat* where an agent finds the percentage between two previously received offers then multiplies that percentage by its last offer. For example, if $\delta = 1$ and the last received offers by a seller agent are \$18 and \$16 at $t = 1$ and $t = 3$ respectively and the buyer agent offered \$10 at $t = 2$ then the buyer agent will propose $(18/16) * 10 = \$11.25$ at time $t = 4$. Equation 2.8 is applicable when $n > 2\delta$. The δ in the *TFT* tactics determines whether an agent imitates the recently received offers or the offers received some time back in the history of the current encounter. If δ is small then the agent imitates the recently received offers. In the following three equations, If $IV^{\mathbb{d}}_{j_l} < RV^{\mathbb{d}}_{j_l}$ then $min^{\mathbb{d}}_{j_l} = IV^{\mathbb{d}}_{j_l}$ and $max^{\mathbb{d}}_{j_l} = RV^{\mathbb{d}}_{j_l}$, otherwise $min^{\mathbb{d}}_{j_l} = RV^{\mathbb{d}}_{j_l}$ and $max^{\mathbb{d}}_{j_l} = IV^{\mathbb{d}}_{j_l}$. Finally, the $Max(.,.)$ is a function that returns the maximum value of its two arguments and $Min(.,.)$ is a function that returns the minimum value of its two arguments.

$$x^{t_{n+1}}_{\mathbb{d}\to\mathbb{s}}[j_l] = Min(Max(\frac{x^{t_{n-2\delta}}_{\mathbb{s}\to\mathbb{d}}[j_l]}{x^{t_{n-2\delta+2}}_{\mathbb{s}\to\mathbb{d}}[j_l]} x^{t_{n-1}}_{\mathbb{d}\to\mathbb{s}}[j_l], min^{\mathbb{d}}_{j_l}), max^{\mathbb{d}}_{j_l}) \tag{2.8}$$

The *Random Absolute Tit-For-Tat* tactic is shown in Equation 2.9. If an agent uses this tactic, it imitates the concessions of its opponent exactly, i.e., in absolute terms. For example, if a seller agent decreases its offer by \$5 then the buyer agent increases its offered price by \$5 too. As said before, it is an exact imitation. A random function ($R(M) \in [0, M]$) is introduced in the tactic where M is the maximum amount by which an agent would deviate from its imitation pattern. The random function $R(M)$ is introduced to break the cycle of exact imitation between agents.

$$x_{\mathbb{d}\to\mathbb{s}}^{t_{n+1}}[j_l] = Min(Max(x_{\mathbb{d}\to\mathbb{s}}^{t_{n-1}}[j_l] + (x_{\mathbb{s}\to\mathbb{d}}^{t_{n-2\delta}}[j] - x_{\mathbb{s}\to\mathbb{d}}^{t_{n-2\delta+2}}[j_l]) + (-1)^s R(M), min_{j_l}^{\mathbb{d}}), max_{j_l}^{\mathbb{d}}) \tag{2.9}$$

Again, the condition for Equation 2.9 applicability is that $n > 2\delta$ since an agent needs to receive a minimum of 2 offers before applying the tactic. In Equation 2.9, if $IV_{j_l}^{\mathbb{d}} < RV_{j_l}^{\mathbb{d}}$ then $s = 0$, otherwise $s = 1$.

The third *TFT* is the *Averaged Tit-For-Tat* (see Equation 2.10) where an agent finds the percentage of an offer received ν steps back in the history of the current negotiation encounter to the most recent received offer then multiply the resultant percentage by the value of the last offered proposal by the agent. When $\nu = 1$, it becomes similar to the relative Tit-For-Tat tactic. If $\nu > 1$, the agent is expected to offer more concessions.

$$x_{\mathbb{d}\to\mathbb{s}}^{t_{n+1}}[j_l] = Min(Max(\frac{x_{\mathbb{s}\to\mathbb{d}}^{t_{n-2\nu}}[j_l]}{x_{\mathbb{s}\to\mathbb{d}}^{t_n}[j_l]} x_{\mathbb{d}\to\mathbb{s}}^{t_{n-1}}[j_l], min_{j_l}^{\mathbb{d}}), max_{j_l}^{\mathbb{d}}) \tag{2.10}$$

The above behavior-dependent tactics model different ways of imitation behaviors. The success of each tactic can be tested empirically. For empirical results concerning these tactics, see [33].

Another formulation is adapted [78] where an agent imitates the concession of its opponent as shown in Equation 2.11. This will be referred to as *Concession Tit-For-Tat*.

$$C_{\mathbb{d}}^t = A * |x_{\mathbb{d}\to\mathbb{s}}^{t-1}[j_l] - x_{\mathbb{d}\to\mathbb{s}}^{t-3}[j_l]| + (1 - A) * |x_{\mathbb{s}\to\mathbb{d}}^{t-2}[j_l] - x_{\mathbb{s}\to\mathbb{d}}^{t-4}[j_l]|\,, \tag{2.11}$$

where C^t is the amount of concession proposed at time t which will be added to the last offer of agent $\mathbb{d}$ if $IV_{j_l}^{\mathbb{d}} < RV_{j_l}^{\mathbb{d}}$ and deducted from the last offer when $IV_{j_l}^{\mathbb{d}} > RV_{j_l}^{\mathbb{d}}$. A is the imitation factor, $A \in [0, 1]$. Formula 2.11 assumes the absolute value in the difference between the last two offers in order to accommodate for all types of issues, i.e., whether their values are increasing or decreasing during negotiation.

To illustrate using Equation 2.11, assume that the turn is for agent $\mathbb{d}$ to propose an offer where it sets $A = 0.6$. It means that the amount of concession (C^t) that will be offered by agent $\mathbb{d}$ at time t consists of 60% of its previous concession and 40% of its oppnent's previous concession. If $A = 0$, then agent $\mathbb{d}$ imitates the exact concession of its opponent and if $A = 1$ then it offers the same amount of concession it offered previously. The concession Tit-For-Tat offers a flexibility to manage the amount of imitation during negotiation by changing the amount of the concession factor A taking into consideration some environmental changes such as behaviour of the opponents, number of out side options etc. In addition, as the previous imitation methods provide the flexibity in selecting recent or old concessions to imitate, the concession Tit-For-Tat also provides the flexibility of sellectig either recent concessions or old concessions to imitate.

In general, an agent takes into consideration the current *negotiation thread* in formulating the behavior-dependent proposals and does not use old negotiation threads generated by previous negotiations.

2.3.3.4 Mixing of Tactics

When an agent uses a single negotiation tactic throughout the course of negotiation to generate proposals, its strategy can be described as a *pure-strategy* or a *non-strategic*. On the other hand, the *strategic* behavior can be either *static* or *dynamic*. The *static strategy* in this context means that an agent first generates multiple offers by different tactics. Each generated offer contributes to the final proposal according to the weight that is previously assigned to each tactic. The weights that mix between tactics do not change during negotiation. In *dynamic strategy*, the weights change during negotiation in response to change in the opponent's behavior [33]. However, for the experimental work of this thesis, the *static strategy* indicates that an agent does not change any negotiation parameter(s) during negotiation regardless of the number of tactics used to generate an offer while the *dynamic strategy* indicates that an agent changes some negotiation parameter(s) during negotiation even if that agent uses a single negotiation tactic to generate a proposal.

To generate an offer, each tactic contributes some percentage (determined by a mixing weight matrix) to the value of the generated offer. For a dynamic strategy, the *mixing weights matrix* are changed according to some factors that form the mental state of an agent. If $MS_{\mathbb{d}}^{t}$ is the mental state of an agent $\mathbb{d}$ at time t and $MS_{\mathbb{d}}$ is the set of agent $\mathbb{d}$'s possible states. The $MS_{\mathbb{d}}^{t}$ combines both knowledge and attitudes. The knowledge is about both the environment and the opponents. The attitudes include goals, designers, intention etc. The change in the mental state of agent $\mathbb{d}$ can trigger a change in the negotiation strategy including the change in the *mixing weight matrix* $\Gamma_{\mathbb{d}\to\mathbb{s}}^{t_{n+1}}$ [35].

$$\Gamma_{\mathbb{d}\to\mathbb{s}}^{t_{n+1}} = \begin{pmatrix} \gamma_{j_1 1} & \gamma_{j_1 2} & \cdots & \gamma_{j_1 h} \\ \gamma_{j_2 1} & \gamma_{j_2 2} & \cdots & \gamma_{j_2 h} \\ \vdots & \vdots & \vdots & \vdots \\ \gamma_{j_p 1} & \gamma_{j_p 2} & \cdots & \gamma_{j_p h} \end{pmatrix} \tag{2.12}$$

A row γ_{j_l} in Equation 2.12 represents the percentages of contributions of different tactics in the generated offer for the issue j_l given that each $\gamma_{j_l,i} \in [0,1]$ and $\sum_{i=1}^{h} \gamma_{j_l,i} = 1$. Agent $\mathbb{d}$ builds the $\Gamma_{\mathbb{d}\to\mathbb{s}}^{t_{n+1}}$ matrix according to its mental state $MS_{\mathbb{d}}^{t}$ at time t.

$$\boldsymbol{\tau}_{\mathbb{d}\to\mathbb{s}}^{t_{n+1}} = \begin{pmatrix} \tau_{j_1 1} & \tau_{j_1 2} & \cdots & \tau_{j_1 h} \\ \tau_{j_2 1} & \tau_{j_2 2} & \cdots & \tau_{j_2 h} \\ \vdots & \vdots & \vdots & \vdots \\ \tau_{j_p 1} & \tau_{j_p 2} & \cdots & \tau_{j_p h} \end{pmatrix} \tag{2.13}$$

The matrix $\boldsymbol{\tau}_{\mathbb{d}\to\mathbb{s}}^{t_{n+1}}$ is the matrix of generated proposals using tactics $\{1,..,h\}$ for each issue $j_l \in J_q$ at time $(t+1)$ by agent a where $|J_q| = h$. Equations 2.12 and 2.13 represent a multidimensional proposal for an object o_i where o_i is characterized by the negotiation issues $\{j_1,...,j_p\}$, i.e., $o_i \sim J_q$. The *weighted proposal* is defined as follows [33].

Definition 2.3. *(***Weighted proposal***) A weighted proposal $x_{\mathbb{d}\to\mathbb{s}}^{t_{n+1}}[j_l]$ is a linear weighted combination of proposals generated by a set of negotiation tactics $\{1,...,h\}$ and defined as: $x_{\mathbb{d}\to\mathbb{s}}^{t_{n+1}}[j_l] = \sum_{i=1}^{h} \gamma_{j_l,i} * \tau_{j_l i}$*

For example, if the vector of negotiation tactic types of an agent $\mathbb{d}$ that is used in a certain negotiation instance (see Section 3.2) to generate proposals for the *price* issue is *<Boulware, linear, conceder, tft>* and the associated weight row vector $\Gamma_{a\to b}^{t_{n+1}}[price] =<$

$0.35, 0.2, 0.15, 0.30 >$ and assume that $\boldsymbol{\tau}^{t_{n+1}}_{\mathbb{d}\to\mathbb{s}}[price] =< 40, 60, 80, 65 >$, then the $x^{t_{n+1}}_{\mathbb{d}\to\mathbb{s}}[price] = 0.35 * 40 + 0.2 * 60 + 0.15 * 80 + 0.30 * 65 = \$57.5$ and agent $\mathbb{d}$ sends $\$57.5$ as a counteroffer to agent $\mathbb{s}$.

A *multidimensional weighted proposal* is a set of *weighted proposals* where $x^{t_{n+1}}_{\mathbb{d}\to\mathbb{s}}[J_q] = x^{t_{n+1}}_{\mathbb{d}\to\mathbb{s}}[j_1], ..., x^{t_{n+1}}_{\mathbb{d}\to\mathbb{s}}[j_h]$. In other words, the multidimensional weighted proposal is a proposal which consists of multiple values (one value per a negotiation issue) where each value is a weighted proposal.

This method of mixing different tactics in generating a proposal has the advantage of incorporating different factors that can play a role in determining the bidding strategy of an agent such as the behavior of the opponents and state of resources, e.g., time. Other external environmental factors that many affect the urgency of reaching an agreement can give more weight, for example, to the conceder tactic etc. When the mental state (MS) of an agent changes, it changes the matrix $\Gamma^{t_{n+1}}_{\mathbb{d}\to\mathbb{s}}$ accordingly. Applying the weighted proposal method by an agent $\mathbb{d}$ decreases the probability of predicting the negotiation strategy of agent $\mathbb{d}$ by its opponent especially when the matrix $\Gamma^{t_{n+1}}_{\mathbb{d}\to\mathbb{s}}$ is dynamic since there will be a regular pattern that can be analyzed by the opponents of agent $\mathbb{d}$.

As stated in Section 4.3, any change to any negotiation parameter is considered a change to the negotiation strategy. The model proposed in this thesis assumes that the $\Gamma^{t_{n+1}}_{\mathbb{d}\to\mathbb{s}}$ is part of the negotiation parameters. Taking into account the mental state of an agent, $\Gamma^{t_{n+1}}_{\mathbb{d}\to\mathbb{s}} = f(MS^{t_n}_{\mathbb{d}}, \Gamma^{t_n}_{\mathbb{d}\to\mathbb{s}})$ where f is a function that takes the mental state and the mixing weight matrix of agent $\mathbb{d}$ at time t and returns $\Gamma^{t_{n+1}}_{\mathbb{d}\to\mathbb{s}}$ that is going to generate weighted proposals at time (t+1). Realizing the function f will be discussed in the following chapters.

2.3.3.5 Trade-off Generation Approach

Trade-off is a concept meaning that one can tolerate losing something for gaining something else. This concept is widely used in real life especially in business. The trade-off approach of generating offers is heavily investigated in the literature of automated negotiation (e.g., [34] [22] [19]). The Trade-off approach is important since it is a method where negotiating partners can use to reach a *win-win* agreement instead of reaching *win-lose* (zero-sum) agreement.

There are two necessary conditions for using trade-off as an offer generation mechanism:

- number of negotiation issues is greater than 1. A negotiating agent should be able to concede on one or more issues and gain on one or more other issues simultaneously
- negotiating agents should have divergent preferences over negotiation issues. This is also an important condition because if all negotiating agents have the same preferences over all issues then there would be no room for using the trade-off mechanism and the game type becomes a win-lose instead of a win-win.

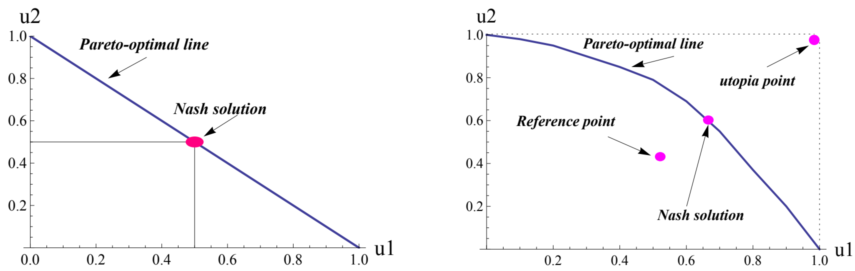


Figure 2.5: *The outcome space for two agents negotiating over a single negotiation issue (left) and multiple negotiation issues.*

Figure 2.5 [34] shows the two utility outcome spaces for two negotiating agents. The first outcome space is for two agents negotiating over a single decision variable (i.e., a single issue) and is represented by a straight line. The second utility outcome space is for two agents negotiating over multiple decision variables (i.e., multiple negotiation issues) and is represented by a curve with a curvature.

Each figure in Figure 2.5 shows the *Pareto-optimal line* and *Nash solution* or *Nash product*. Any outcome that lies on the Pareto-optimal line is considered an efficient solution. The Nash solution selects a point on the Pareto-optimal line that maximizes the product of the two utilities. In case of a single decision variable, all possible outcomes lie on the Pareto-optimal line. The *Nash solution* in this case is the midpoint where the utility of the first agent ($u1$) is equal to the utility of the second agent ($u2$) assuming that the two agents valuate the gain on that issue equally. In our case, assuming the conflict outcome utility is zero, the Nash solution is achieved when $u1 = 0.5$,$u2 = 0.5$

where $u1 * u2 = 0.25$ which is the maximum possible combination between the two utilities. It is like dividing the cake equally between two individuals. In case agents are negotiating over multiple issues, the Nash solution is the point that is Pareto optimal and lies on the line connecting the *reference point* to the utopia point. The reference point can be computed as the utility outcome at the midpoint of each decision variable [34].

In many real life scenarios, agents are negotiating under incomplete knowledge and it is difficult to find optimal bargaining solutions such as Nash solution. Heuristic methods are used to approximate the preference structure of the opponent as an approach to reach near optimal solutions.

The trade-off generation approach in the context of automated negotiation is associated with terms such as *Pareto-optimality* (see Section 2.2), *social welfare* and *iso-curves or indifference curves*. The social welfare refers to the system utility. Social welfare can be looked at either from the *utilitarian* or *egalitarian* point of views. The utilitarian principle is based on achieving the greatest total welfare. The total welfare of a society is the sum of each individual utility in that society. The egalitarian principle is concerned about maximizing the utility of the most needy individuals in society [97]. For example, Nash solution is considered more utilitarian than egalitarian [114]. kalai proposed a characterization of an egalitarian solution when the bargaining set is convex, compact and comprehensive for a fixed number of individuals [62]. The solution is characterized by being symmetric, having weak Pareto optimality and so strong monotonicity is assumed. An egalitarian solution considers fair outcomes by maximizing the more unfortunate individuals.

The indifference curve consists of the set of *composite offers* over a certain object that have the same utility value. If the negotiation issues are of a continuous type, the number of possible indifference curves are infinite.

Definition 2.4. *(***Composite offer***) A composite offer is an offer that contains more than one value. It happens when a negotiation object is characterized by more than one issue in which case the offer proposed or received for this object is a composite offer.*

For example, a proposed composite offer may contain \$10 for the price issue and 2 *kg* for the weight issue of a certain material. Figure 2.6 shows three iso-curves, $u1, u2$ and

$u3$. For example, all the points on the iso-curve $u1$ have the same utility level. In other words, an agent is indifferent to any composite x and y values that lie on the curve $u1$. The same applies to any iso-curve.

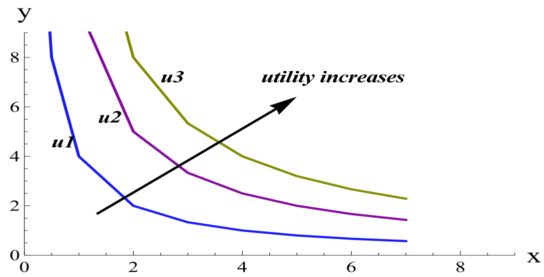


Figure 2.6: *Iso-curves*

For an agent who intends to keep the same aspiration level (i.e., utility value) while negotiating with other agent(s), it can move along its current indifference curve trying to propose offers with higher values to its opponent(s) given the fact the agents have divergent preferences over issues. For example, consider a buyer agent and a seller agent. Both are negotiating over an item containing the *price* and *delivery_time* issues. The seller agent needs a long time to deliver the item and is willing to concede more on the *price*. On the other hand, the buyer agent is more concerned about the *price* and is willing to concede more on the *delivery_time* than the seller agent who may give more concessions on the *price* and less concessions on the *delivery_time* which suits the buyer agent's preferences.

As a negotiation strategy, an agent should stay on its current indifference curve as much as it can. The agent can stay on its current indifference curve without causing the opponent agent to withdraw from negotiation by proposing trade-off offers that may provide the opponent with more valuable offer(s) than the ones proposed previously. Given the fact that agents negotiate under incomplete knowledge, since the utility structures, reservation values and deadlines are considered private information for each, different methods are used to approximate the preference structure of the opponent in the process of generating offers that may give higher values to the opponent than the previously offered ones while staying on the current indifference curve.

Besides the *mediated-negotiation* (e.g., [31]) in which agents disclose some information to a trusted third party that helps in reaching a Pareto-Optima agreement (or near Pareto-optimal) agreements, the *similarity* (e.g., [34]) methods such as fuzzy similarity and *shortest-distance* (e.g., [73]) approaches are proposed to reach a near Pareto-optimal outcome in multi-issue negotiation. In addition, the *iterative-offer-generation* is a proposed method that enhances the chances of proposing offers that are of more value to the opponent than the previously proposed ones [87]. The iterative-offer-generation mechanism is discussed in Section 6.2.

The *mediated-negotiation* proposed in [31] searches for an optimal-agreement in bilateral negotiation where the negotiation issues are of a continuous type. The mediator takes into consideration the preferred directions submitted by the two negotiating agents. In each negotiation round, the mediator receives two proposals from the two agents then it generates a new tentative agreement taking into consideration the jointly improving direction. The negotiation process continues until the optimal solution is found. However, due to the practical problems associated with using a mediator such as trust, in many situations, it is difficult to use the mediated-negotiation approach.

The idea of using similarity between offers is investigated in [34]. The proposed algorithm uses the fuzzy similarity principle to approximate the preference structure of a negotiating opponent by modeling the domain of the decision variables. The hill-climbing technique is used to search the apace of possible trade-offs for the offer that is most likely to be acceptable by the opponent. It is easy to find similarity between continuous issues such as a price, since if the difference between two prices is zero, then the similarity is maximum. The problem in measuring similarity between the values of issues happens when the negotiation issues are of discrete types. For example, a color can be an issue of negotiation. The color domain can be a set containing red, blue, yellow, green, etc. The problem is that how can one measure the similarity between two colors such as red and blue? Faratin et al. propose creating a set of criteria functions that can be used to associate each color in the color domain with a specific number representing a certain criteria such as "warmness" of colors [34]. When an agent decides on using the trade-off method, it generates a few counteroffers then it selects the most similar one to the last received offer from the opponent given that the agent generates the counteroffers at the same previous utility level, i.e., the agent stays on its current indifference curve. However, the method needs some knowledge about how the opponent places weights on the different issues. In addition, it is difficult to find suitable techniques to measure similarity between discrete negotiation issues.

The *shortest distance* approach [74] finds the shortest distance between the last received offer and an offer on the current indifference curve. The empirical experimental results presented in this paper show that agents achieve near Pareto optimal agreements by using the shortest distance approach given that the negotiation issues are of a continuous type. The preference of each agent is rational and strictly convex and the monotonicity behavior is assumed. However, the negotiation model requires that agents stay enough time in negotiation and propose a number of offers (to increases the chances of finding a proposal that is close enough to the last opponent's offer) in each negotiation round. In addition, the approach assumes that both agents capture their preferences using utility functions. However, in many real cases, agents can not characterize their preferences by a utility function, because this function may not exist. Moreover, it is not clear when an agent should move from the current indifference curve to another indifference curve. In addition, it is not clear how efficient the technique is in case the number of negotiation issues is large. Other trade-off approaches are proposed, for example [119] assumes that negotiation issues have binary values in estimating the opponent's utility structure.

2.3.4 Argumentation-Based Negotiation

Argumentation-based negotiation (ABN) is a relatively new approach where agents exchange not only offers/counteroffers but also *arguments*. The arguments are pieces of information that aim to change the mental state of an opponent. Changing the mental state of an agent using an argument can be achieved by either *justifying* the proposed offer or *persuading* (influencing) the opponent's point of view or stance [59]. The influencing argument could be a promise for reward or a threat. For example, when a project manager asks his/her employee to finish a task within a short period of time, then the employee might disagree to that request as he/she needs more time. In this case, the manger may promise a financial reward if the employee finishes the task within a short period of time or threat to fire the employee if the task is not finished within the requested time frame. An agent using the argumentation-based method may ask to change the negotiation object or add more attribute(s) to the current negotiation object. For example, if an employee asks his/her manager a pay raise then the manager may reject the request. To overcome this problem, the number of working hours attribute can be introduced to the negotiation as an argument where the employee asks to keep the same rate of pay while reducing the working hours etc. [160].

People usually use the argumentation concept during their daily negotiation interactions. For example, a customer who would like to buy a laptop can visit different shops to check prices and other related data. Then he/she can use the collected information as an argument with a new shop manager saying that "*I found a similar laptop with a price of $330 and you are asking for $340*". This type of argument may convince the shop owner to beat that price and sell that laptop for less than $330. If the customer does not know about the prices of that type of laptop in other places, then convincing the owner of the current store to sell that laptop for less than $330 would be more difficult.

Since the classical negotiation approaches (i.e., game-theoretic and heuristic) of conflict resolution in multiagent systems focus on exchanging potential proposals according to different protocols or on mechanism design that have limitation in achieving the goal(s) of negotiation, argumentation-based negotiation can improve both the chance of reaching an agreement and the quality (in terms of utility, fairness etc.) of the agreement for agents engaged in negotiation. In general, agent using game-theoretic or heuristic models are allowed only to exchange proposals; agents are unable to exchange additional information to persuade or influence other agents. In case agents have limited information about the environment and/or about other agents especially when the rational choices of some agents depend on the choices of other agents, the traditional methods of negotiation-based conflict resolution limit the quality of the negotiation outcomes [160].

The ABN approach has the potential to improve the outcomes of the negotiation process when compared to the game-theoretic and heuristic approaches since the proposals exchanged between agents during negotiation is richer in terms of information. However, the drawback of the ABN lies in the added complexity in design and implementation of the ABN frameworks. It is obvious that the process of generation, selection and evaluation of arguments by agents is nontrivial. Several ABN models were proposed in the literature [111][72][133][1] that target several dimensions of the ABN complexity. Some models are based on psychology of persuasion using threats, rewards and appeals (e.g., [72]) and assume agents use utility functions and have the same architecture while the protocol is implicit in the agent's specification. On the other hand, the argumentation style is logic-based in [111] and the protocol is designed as a finite state machine and allows generic meta-information to be passed amongst agents. A more recent ABN framework [1] is proposed which formally defines the link or relationship between the status of the arguments and the offers they support. In addition, it defines the notion of concession and its effect on the course of negotiation. The work also investigates how the theories of agents evolve during negotiation. However, the work assumes that the agents have the same set of offers and compare their offers similarly which are strict assumptions.

Modeling the argumentation process as a planning problem is presented in [95]. The output of the process is argumentation plan. The authors propose constructing a partial order of arguments that allows an agent to reach an expected agreement if the agent utters the arguments according to the specified partial order in a certain negotiation situation. To build the argumentation plan, a planning algorithm based on preferences of an agent were proposed. The proposed framework evaluates the argumentation plan rather than the individual arguments. A limitation to the presented approach is that an agent needs certain information especially about the opponents to build a robust argumentation plan.

An agent negotiating with multiple opponents concurrently can use arguments similar to the one given in the previous example to strengthen its bargaining power and convince other opponents to agree on proposals presuming high value to the arguing agent or to all agents. However, the ABN is not the subject of this thesis. An argument-based approach in one-to-many negotiation will be left for future work.

2.4 Dependencies and Coordination

Interdependency between related activities is the driving force behind the need for coordination. Malone and Crowston define coordination as "managing dependencies" [84]. The dependency and coordination are two related concepts since coordination becomes an important task when the dependencies cause problems.

Figure 2.7 [84] shows a classification of possible dependencies between related activities that can apply in different application domains. According to Figure 2.7, several types of dependencies in the automated negotiation domain can be identified. Since this thesis investigates the problem of coordinating multiple negotiations running concurrently, the activities considered in this context are the set of actions that can be taken in each single negotiation encounter such as accepting a proposal or offering a counter proposal.

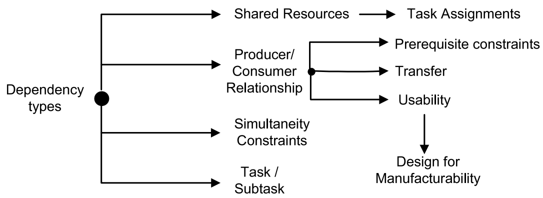


Figure 2.7: *Common dependency types*

Objects under negotiation may *share resources*, for example, an agent negotiating for buying a laptop and a camera needs to allocate a certain amount of the available money (a resource) for buying the laptop and another amount for buying the camera. In that sense, the laptop and the camera share a resource. The agent needs to distribute/redistribute the resource in a way to achieve the negotiation goal, i.e., reach a valuable agreement.

The *task assignment* dependency that is related to the shared resources dependency appears when multiple agents negotiate over performing different tasks. Different tasks may require different resources and/or different amounts of resources. Accordingly, task assignment is related to the distribution of certain resources, i.e., the assignment of tasks to agents is related to the type and/or amount of resources allocated to each agent. From a different point of view, when resources can be shared, multiple agents can use the same resource at the same time, e.g., multiple agents may access and read the same document (a resource) at the same time.

The *prerequisite constraints dependency* exists when one activity must be completed before another activity can start or finish [84]. When an agent seeks to buy a hardware and a software given that both the hardware and software must be compatible, it can select to buy the hardware first then buy a compatible software or vice versa since buying both simultaneously may result in buying incompatible products.

The *simultaneity constraints* dependency determines which negotiations can run concurrently and which negotiations should not run concurrently. In other words, the process of running different negotiations or taking certain actions during negotiation such as quitting a certain instance of negotiation needs to be synchronized.

The *task/subtask dependency* in a negotiation process can be illustrated when one negotiation depends on some other negotiations, i.e., the negotiations are multi-linked [165]. For example, if there are 3 negotiations a, b, c, but negotiation a depends on negotiations b and c (i.e., negotiation a is successful iff negotiation a is successful and both negotiations b and c are also successful), then we consider that negotiation a has two subtasks (i.e., b and c).

One of the most complicated activities during negotiation is deciding on the value of the next proposal by an agent. During negotiation and for each negotiation round, an agent needs to select a bidding strategy that can generate the next proposal, i.e., generate an offer or a counteroffer. Calculating the value of an offer/counteroffer in each negotiation round is a non-trivial process due to the following:

- the process can be affected by the actions of the outside options
- the interdependency between the issues of the same object
- the interdependency between the issues of different objects
- the interdependency between different negotiation objects.

In the next next two sections, there will be more elaboration on the interdependency in the one-to-many negotiation considering the dependency from the point of view of a buyer agent negotiating concurrently with multiple seller agents.

2.4.1 Interdependency Amongst Objects

Sometimes, it it important to procure a certain number of objects in a certain order when the objects are interdependent. The interdependency between objects results from the precedence relation between the objects. For example, hardware and software objects can be interdependent due to the compatibility issues between softwares and hardwares. In many cases, software needs to run on compatible hardware and hardware has some requirements for the software it can operate. In this case, procuring the hardware first has an effect on the type of software that is going to be procured and vice versa. Solving the problem of procuring different objects with precedence constraints can be solved either by sequential negotiation or by concurrent negotiation.

Accepting a number of agreements by an agent in a certain order while negotiating concurrently with multiple opponents is equivalent to achieving the same number of objects in the same order while negotiating with opponents sequentially. Procuring a certain number of objects sequentially is the easiest solution to solve the problem of procuring a certain number of objects in a certain predefined order. However, using the sequential approach has a few drawbacks. Firstly, because negotiations are conducted once at a time, it is difficult to predict the results of the future negotiations in terms of: 1) whether a certain negotiation instance will be able to reach an agreement 2) the expected utility of the agreements. Secondly, it is difficult to allocate resources for each negotiation instance because we have no knowledge about the demand behavior of the opponents of the future negotiations. For example, we might allocate more resources for the first few negotiation instances to guarantee reaching agreements but the resources for the next negotiations may not be enough to guarantee reaching agreements over the rest of the objects. Finally, the sequential approach takes more time.

An alternative solution to the sequential negotiation approach is adopting the concurrent negotiation approach where a negotiating agent receives feedback during negotiation in terms of the opponents' offers and can act accordingly to fine tune its strategy and resource allocation pattern. The drawback of the concurrent approach is the need for coordination whenever any type an of interdependency exists between objects or between objects' issues, etc. For example, different objects may have interdependency between their attributes such as interface compatibility between two different softwares. Sometimes buying object (o_1) before buying object (o_2) causes a loss in utility such as confirming a hotel reservation before confirming a flight. If the flight is canceled for any reason then the buyer might be obliged to fulfill his/her obligations towards the hotel reservation.

In some cases, the order of procurement is not defined before the start of negotiation, it could be determined dynamically during negotiation. For example, a person needs to book a flight and an accommodation before starting his/her vacation and at the same time, he/she does not know which one is more difficult to find. During negotiation, the agent working on the behalf of that person detects which one is more difficult to secure and decides the order of agreements and resource allocation dynamically. The agent may find that booking a flight is more difficult than booking an accommodation, then it decides to secure an agreement for booking the flight first.

2.4.2 Interdependency Amongst Issues

Each object under negotiation is characterized by one or more negotiation issues or attributes. The interdependency between two (or more) issues results from existing relations between them in the sense that the utility of an agreement on the two issues together is greater than the sum of the utilities if the two agreements are achieved in disjunct manner. This type of interdependence is called *preferential dependency* [92] since the utility of an issue depend on the value of one or more issues. For example, a flight can have two issues, the *day-of-the-flight* and the *time-of-the-flight*. Assume that a certain passenger prefers to fly on Friday before 12PM. The travel agency says there is a flight available on Thursday before 12PM and another one is available on Friday after 5PM. To evaluate the situation, the utility of flying on Friday before 12PM is more than the sum of the utilities of flying on Thursday before 12PM and the utility of flying on Friday after 5PM. This type of relation between the issues of *day-of-the-flight* and *time-of-the-flight* is called *complementary* relation, i.e., the issues complement one another. Moreover, different issues can be interdependent in terms of their acceptable values. For example, an agent may agree to pay a high price for a high quality product.

When the number of negotiation issues is large, it becomes difficult to search for a proper combination between the values of issues since the search space becomes large. When the issues are of a continuous type, the search problem becomes even more difficult and intractable. Utility functions without preferential dependencies have a simple linear structure (weighted average) with a single optimum value. On the other hand, utility functions with preferential dependencies often have a nonlinear behavior with multiple optima structure.

Apart from dealing with the problem of searching for the best offer that can achieve the highest possible utility in case the utility function is nonlinear, we focus on the problem of allocating shared resources amongst different negotiation issues. In many cases, the distinct objects can have the same issue such as price. In our work, we call the issues of different objects that share the same resource as *common issues*.

Definition 2.5. *(***Common negotiation issue***)*

A common negotiation issue is an issue $j_i \in \mathbf{J}$ s.t. at least two subsets $J_k, J_l \in 2^{\mathbf{J}}$ exist where $j_i \in J_k \cap J_l$. $\mathbf{J}$ is the set of negotiation issues.

In other words, a *common issue* is an issue that is common amongst multiple objects. For example, multiple services can have the price issue as a *common issue*.

To this end, we propose managing resources shared amongst *common issues* as an approach for coordinating the bidding strategy which takes into consideration the behaviors of the opponents over the *common issues*, see Section 4.3. Managing the distribution of the available resources (which is part of the bidding strategy) is one solution for managing the interdependency problem.

2.5 Coordination and Negotiation

Negotiation is a potential mechanism for agents to use for coordinating their actions. A possible classification of coordination types is shown in Figure 2.8. In the *centralized coordination*, all agents report to a central authority that make decisions by looking at the coordination problem globally. The main drawbacks of the centralized coordination are the single point of failure and the trust problems. The single point of failure means that if the central authority fails, the entire system will stop working. In a community of heterogeneous agents, it is difficult to apply the centralized coordination approach since agents can have different and conflicting goals and agents find it difficult to have a trust in a third party to coordinate their actions. The *hierarchy coordination* is similar to the centralized coordination except that in hierarchy coordination, there are different levels in the decision making process and each level needs to report to the upper level and different levels in the hierarchy can be responsible for different types of decisions. Ossowski and Menezes [110] present the term *emergence coordination* which indicates that the solutions to the coordination problems emerge from the interaction between agents (or processes) in which an agent tells the other agents about its actions without expecting a direct consequence from that interaction. Such coordination mechanisms can be efficient in particular games such as the minority game [8]. However, negotiating agents are affected directly by the messages (proposals) exchanged between them.

In multiagent systems, the focus is on the decentralized coordination. The decentralized coordination is a more interesting approach since it does not have the drawbacks inherited in the centralized coordination approaches. In addition, agents can be more

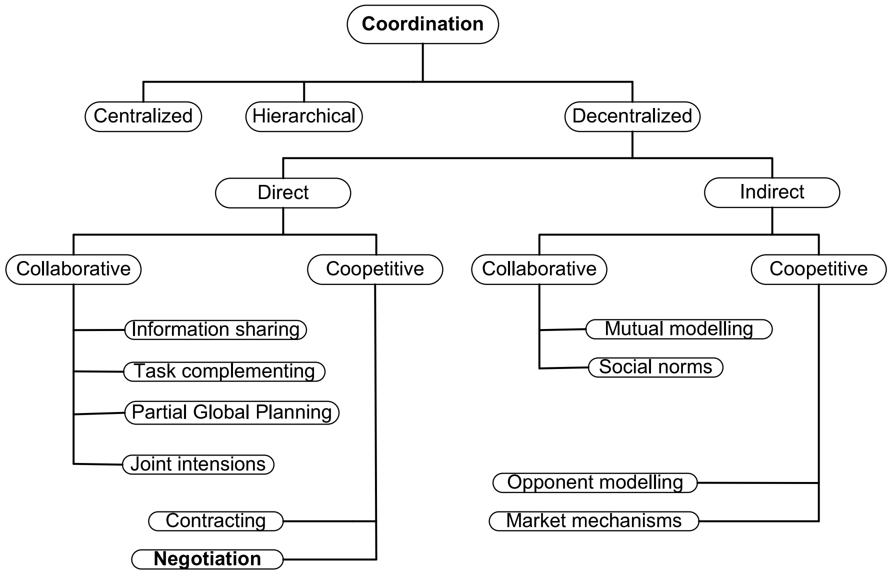


Figure 2.8: *Categorization of coordination in multiagent systems*

autonomic and can interact, compete and cooperate to reach mutual decisions or can react to the changes in the environment or follow certain rules that guide them to a well coordinated situation.

The decentralized coordination can be divided into *direct* and *indirect* subcategories. The direct negotiation means that agents coordinate their actions by direct interactions amongst themselves. On the other hand, in the *indirect coordination*, agents do not interact directly but they follow some rules and regulations or interact to some environmental changes. In other words, agents interact with the environment in which they are situated in. Keil and Golden define direct interaction as "interaction via messages, where the identifier of the recipient is specified in a message" and indirect interaction as "interaction via persistent, observable changes to a common environment; recipients are any agents that will observe these changes" [66].

Collaborative and coopetitive coordination approaches are found in both direct and indirect coordination. The *mutual modeling* is a coordination approach where agents try to model the behavior of other agents in a given situation. This approach was first defined formally by Genesereth et al. and called *cooperation without communication* [45]. As the utility of one agent depends on the action(s) of other agent(s), the joined actions of agents determine the utility of each agent. If two agents are interacting without communication, Genesereth et al. show that an agent can benefit from the information gathered about its opponent by determining its rational action(s) and acting accordingly [45]. If the aim of the agents is to achieve a common goal the mutual modeling is the name of the approach. If agents have different goals, then the opponent modeling is the name of the coordination approach which is similar to the mutual modeling except that the mutual modeling is used in a totally collaborative environment. Market mechanisms can involve both cooperative and competitive behaviors.

The *social norms* is another collaborative coordination approach where agents adhere to some norms (which are established or expected) during the interaction. For example, it is a social norm for a student to raise his/her hand before asking a question while in a class. On the other hand conventions or social laws can be either designed offline or emerge from within the system. For more information about emergence from within the system social laws, see [158].

The *information sharing* is a collaborative coordination approach where agents share information and try to coordinate their tasks accordingly. For example, a set of agents can share and exchange information about each others skills and expertise before assigning a certain set of tasks. In *task complementing*, agents collaborate in the process of task assignment in a complementary fashion where agents are assigned task(s) in which their expected performance is high. Factors like an agent's resources and the expertise of each agent are taken into consideration in the process of task assignment.

The *partial global planning (PGP)* is a distributed control technique to ensure that the local plan of each node in a network is coherent with the local plans of the neighbouring nodes assuming that each node in the network represents an agent [29]. It is called partial because agents do not aim to generate a plan for the whole system and it is called global because agents exchange local plans to form non-local plans. The partial global planning consists of three repetitive steps: 1) each agent generates short-term plans that aim to achieve a predefined goal(s) 2) agents exchange information that help in updating their short-term plans 3) agents modify their short-term plans. The *PGP* is extended into *generalized partial global planning* that makes use of five techniques to coordinate agents' activities: Updating non-local viewpoints, communicating results, handling simple redundancy, handling hard coordination relationships and handling soft coordination relationships [25][159].

The *joint intention* coordination is a technique that considers the intentions of agents in terms of their planning doing certain work. Intentions can provide stability, predictability, flexibility and reactivity. The first two points are important for the social interaction while the latter two points are important to cope with a changing environment [159]. Jennings developed and implemented the *joint responsibility* coordination model that is based on joint intentions. Before commencing the joint problem solving process, the defined preconditions must be satisfied. The joint responsibility model assumes that each individual within a system needs to stay committed to using the agreed upon solution to achieve the common goal until one of a set of events is fired, such as the objective has been met, the objective will never be met etc. If a team member agent decides to decommit its responsibility, it must ensure that all of its team members are aware of the new status to enable the rest of the team to reassess the new situation and judge the viability of the joint action especially the actions that are supposed to be carried out by the decommitted team member [56].

The *contracting* is a coordination method that can apply in a situation where a group of agents compete for a certain number of tasks. The Contract Net (*CNET*) protocol is "a high level protocol for communication among the nodes in a distributed problem solver" [142]. To apply the *CNET* protocol as a task allocation mechanism amongst a group of agents, tasks are announced by a manager agent. Then each group member bids for one or more tasks, and finally the manager allocates tasks. The agents who are selected to perform tasks are called contractors. Each contractor agent sends a report to the manager after the completion of its allocated task(s). It is possible for a contractor agent to subdivide its tasks and play the role of a manager by announcing the new subdivided tasks. An agent's decision to bid on new tasks depends on the marginal cost calculations. If the marginal (extra) cost is less than or equal to zero, then it is rational for the agent to bid on the new tasks, otherwise it is not rational to bid on the new tasks since the agent would need more resources to complete the new bids than what it has. This protocol was inspired from the way that organizations usually put contracts out to tender [159].

As shown in Figure 2.8, negotiation is considered a *coopetitive*, *direct* and *decentralized* coordination mechanism. Negotiation is coopetitive because agents can compete and cooperate during negotiation. For example, agents cooperate when they use the trade-off negotiation mechanism to reach an agreement and compete when they need to concede to reach an agreement. Negotiation can be direct when agents interact with each other directly without any mediation mechanism. It is decentralized since agents synchronize their actions by interacting with each other without a central decision making authority. In other words, the decision making mechanism is distributed since each agent can participate in reaching the final agreement(s).

The relationship between negotiation and coordination is presented from a new angle here. Negotiation is listed as one mechanism in which agents can use to coordinate their actions, see Figure 2.8. This thesis considers a buyer agent negotiating concurrently with multiple seller agents and since the buyer agent is interacting with multiple agents concurrently, its actions need to be coordinated to achieve the overall goal of negotiation. During negotiation, the buyer agent receives multiple offers from a group of seller agents. Consequently, it needs to decide how to react to each agent since the different negotiation instances (see Section 3.2) can be interdependent. For example, when the buyer agent receives 4 different offers simultaneously, it can accept the best one of them and quit negotiation. On the other hand, there is a possibility for the buyer agent to receive a better offer from other agent(s) if it stays in negotiation. The buyer agent can monitor the level of concessions offered by each agent by inspecting the current negotiation threads and deciding what to do next. For example, when the behaviors of the seller agents vary, this can be a favorable situation to the buyer agent since it means the chance for receiving a better offer in the future is high. It can be concluded from this example that different negotiation instances can be interdependent from this point of view. In addition, Section 2.4 discusses possible dependency types in negotiation. One of the important dependency types that is investigated in this thesis is when one or more issues of different objects share a resource. For more detail on the coordination problem in one-to-many concurrent negotiation, see Chapter 4.

Since the focus of this thesis is on the bidding (bargaining) strategies in the one-to-many interaction where a buyer agent is negotiating concurrently with a set of seller agents over one or more negotiation objects, the following few sections discuss the related work and present and analyze different negotiation strategies that are proposed in the literature to coordinate the one-to-many negotiation.

The sections are divided according to the number of negotiation issues and/or a number of negotiation objects under negotiation. This division is chosen to facilitate the presentation of the related work since the number of negotiation issues and/or the number of negotiation objects have an effect on choosing a certain negotiation strategy. For example, if agents are negotiating over a single issue, then the trade-off negotiation tactic is not an option. When agents are negotiating over multiple objects, the issues of the objects may share a resource in which the allocation of that resource needs to be coordinated dynamically during negotiation.

2.5.1 One-to-Many Negotiation Over a Single Issue

In the context of business negotiation, the single issue negotiation is the most investigated type of negotiations where in most cases the single issue represents the price issue. This section discusses various methods proposed in the literature concerning the one-to-many negotiation over a single continuous issue.

In their proposed one-to-many negotiation model, Rahwan et al. [115] propose four coordination decision making mechanisms for a buyer agent negotiating with multiple seller agents concurrently: 1) *desperate strategy* in which the buyer agent accepts the first acceptable agreement and quits negotiations with all other sellers, hence it is called desperate 2) *patient strategy* where the buyer agent makes temporary agreements with some of the seller agents during negotiation and holds on to these agreements until all the remaining instances of negotiations are finished, then the buyer agent selects the agreement with the highest utility and renege from all other agreements 3) *optimized patient* strategy is similar to the patient strategy except that it does not accept a new agreement with less utility than the highest acceptable one 4) *manipulation* strategies in which the coordinator entity in the buyer agent changes the negotiation strategies of its sub-negotiators during negotiation. Changing a negotiation strategy means adapting one or more of the negotiation strategy parameters, see Chapter 4.

The first three strategies (i.e., desperate, patient and optimized patient) assume that the buyer agent has the privilege of reneging on temporary agreements without penalty. This assumption can be realistic in situations where the number of seller agents is large and/or the seller agents are offering infinite supply, e.g., information. In such cases, a seller agent might be satisfied to make deals with many potential buyers in hope that some of the buyers will confirm their deals later. The other two agreement handling rules are: an agent can renege from an agreement and incur a penalty to be paid, the second one is that an gent must honor its agreement(s) which means an agent must be committed to executing its agreement(s).

If reneging on an agreement incurs a penalty, the processes of deciding to make a temporary agreement and reneging on agreement needs to be analyzed carefully. In other words, a commitments/decommitment mechanism is required. A rational agent can only renege on a temporary agreement if and only if the utility of the new agreement(s) is larger than the utility of the temporary agreement plus the incurred reneging penalty. The amount of penalty can be either a fixed amount that is agreed upon by negotiation partners or dynamically calculated according to a certain formula. Empirical results show that when agents use a dynamic method to calculate the amount of incurred penalty, they can be more flexible in deliberating about their behaviors that results in gaining a better negotiation outcomes than using a fixed amount [105].

Managing commitments in concurrent negotiation is investigated in the literature, e.g., [105][2]. Nguyen and Jennings [105] propose a commitment model that considers calculating the amount of penalty according to equation 2.14.

$$\rho(t)^{\mathbb{d}} = U(x^{t_{\mathbb{s}}}_{\mathbb{s}\to\mathbb{d}}) \times \Big(\rho_o + \frac{t - t_{\mathbb{s}}}{t^{\mathbb{d}}_{max} - t_{\mathbb{s}}} \times (\rho_{max} - \rho_o)\Big), \tag{2.14}$$

where $\rho(t)^{\mathbb{d}}$ is the penalty fee that has to be paid by the agent $\mathbb{d}$ at time t, $U^{\mathbb{s}}(x^{t_{\mathbb{s}}}_{\mathbb{s}\to\mathbb{d}})$ is the utility value of the offer $x^{t_{\mathbb{s}}}_{\mathbb{s}\to\mathbb{d}}$ calculated according the utility function of the agent $\mathbb{d}$, ρ_o is the fee that needs to be paid if the deal is broken at the contract time ($t_{\mathbb{s}}$). Finally, ρ_{max} is the fee that needs to paid if the deal is broken at the execution time which is considered the agent's $\mathbb{d}$ deadline. It is a common sense that if an agent breaks a deal at the execution time, the harm to the contractee agent is maximum and so the penalty fee should be. According to equation 2.14, the penalty is maximized if an agent breaks a deal at its deadline. The agent $\mathbb{d}$ may commit (accept) a new offer and renege on an existing offer (if it exists) if $U(x^{t}_{\mathbb{s}'\to\mathbb{d}}) > U(x^{t'}_{\mathbb{s}\to\mathbb{d}}) + \rho(t)^{\mathbb{d}}$, $t > t'$ and the degree of acceptance for the offer $x^{t_{\mathbb{s}}}_{\mathbb{s}'\to\mathbb{d}}$ is higher than a certain predefined threshold. Even though the model of calculating the penalty fee is a dynamic since it takes into consideration the time elapsed, it is not clear that how genuine an agent can be in declaring its $U^{\mathbb{s}}(x^{t_{\mathbb{s}}}_{\mathbb{s}\to\mathbb{d}})$ value since the preference over an outcome is considered a private information. In addition, it is not clear how an agent can determine the value of the threshold.

In their work, An et al. [2] consider the problem of resource allocation in a dynamic environment like the cloud computing platforms and propose a negotiation mechanism where agents negotiate over a price of a resource and a decommitment penalty of reneging on a contract. The rule proposed to determine the decommitment penalty is: The lower the price, the higher the penalty. This rule can be a practical one. For example, a seller may agree to offer a resource with a low price in exchange for receiving a high penalty fee if the buyer agent decides to renege on the agreement. In this way, the seller agent either sells its resource or receives a good payment from the buyer in case it reneges on the agreement. When a buyer agent needs a set of resources and no one seller agent can fulfill its demand, the experimental results show that the optimum strategy for the buyer agent is to make two sets of agreements. A possible reason is that the buyer agent needs to pay larger penalty fees when it makes more agreements since it needs to confirm one set of agreements and decommit all other agreements at its deadline. On the other hand, if the buyer agent makes one agreement, some seller agents may decommit some agreements and the buyer agent will not be able to complete its tasks because of shortages in resources. For more information on commitment management in automated negotiation see [129] [136].

This thesis does not consider the negotiation situation where agents incur a penalty when reneging on temporary deals. However, it does consider managing the negotiation strategy for the other two agreement rules: firstly, an agent has the privilege to decommit an agreement without incurring a penalty. Secondly, the agents must honor their agreements. Even though giving an agent the right to decommit a previously agreed upon contract (with penalty) would give more flexibility to the agent to adapt to the new changes in the environment, the other agreement rules are more common in the literature.

The outside options in the multi-bilateral negotiation can affect the negotiation strategy of an agent because of the possible interdependent relationships amongst different negotiation instances as discussed earlier. To study such interdependencies, Li et al. investigate the effect of outside options on the negotiation strategy of a buyer agent negotiating concurrently with multiple seller agents where the agreements are considered binding to the negotiating agents [23]. Knowledge of an opponent's reservation value on an issue such as price can change the mental state of an agent which results in changing its negotiation strategy by changing its reservation price towards a higher utility reservation price. The objective for the buyer agent is to achieve a single agreement with the highest possible utility. The important parts of the study consider the one-to-many negotiation and investigate two situations: the first situation is when a buyer agent is negotiating concurrently with a number of seller agents and new seller agents are not expected to join negotiation. In this case, the buyer agent has a number of negotiation threads equal to the number of seller agents. In this case, the buyer agent assigns to each thread a reservation utility value equal to the expected utility from the multi-threaded negotiation formed by all other threads. From one thread's perspective, all other threads are considered outside options and form a synchronized multi-threaded negotiation. The study proposes four heuristics to estimate the expected utility from a synchronized multi-threaded negotiation. Three of them (conservative estimation, medium estimation and uniform approximation) use the reverse English auction theoretical analysis results in the approximation process for the expected utility in the synchronized multi-threaded negotiation. The proposed mechanisms are based on the assumption that the buyer agent has a prior belief about the probability distribution of each seller agent's reservation price. The fourth mechanism is a learning mechanism that depends on the outcomes of previous negotiations. The study assumes that the data comes from the market survey or from data of a third party. The proposed learning mechanism approximates the expected utility from a multi-threaded negotiation by estimating the expected utility from the most competitive thread in a single negotiation. For more detail, see [23].

The second situation is the dynamic multi-threaded negotiation where the buyer agent is negotiating concurrently with multiple sellers and more seller agents are expected to join the current negotiation. In that case, the bargaining power of the buyer agent becomes better. The outside options for a negotiation thread in this case includes both, the current outside options and the negotiation threads that can be initiated in the future by the new arrived sellers. The arrival pattern of the outside options is assumed to follow a Poisson process. The assumption about the arrival probability along with the probability distribution about the opponents' values that are expected to arrive in the future are used by the buyer agent to forecast the number and the quality of the outside options arriving. The work presented in [23] demonstrates how multiple negotiation instances can be interdependent. The drawback of the described work is in the previous knowledge assumption about the probability distribution about the opponents' reservation prices and about the value of the seller agents that might join the current negotiation which are necessary for the described approaches. In open and dynamic automated negotiation systems, such knowledge is difficult to attain.

The Markov chain model is proposed as a decision making mechanism in the one-to-many negotiation where a buyer agent is negotiating with multiple seller agents concurrently and the agreements are considered binding to agents. An et al. propose a decision making strategy based on Markov chain model (Markov chain based decision making *MCDM*) of a negotiation process [3]. The *MCDM* considers the dynamics and uncertainties of the negotiation process using stochastic modeling of the negotiation process. The aim of the *MCDM* mechanism, at each negotiation round, is to decide whether to accept the best available offer and quit negotiation or to proceed with negotiation for the hope that the buyer agent would receive an offer(s) with better value(s). Again, the study presents a model that captures the interdependencies amongst the negotiation instances or threads. In their work, An et al. consider the price issue as the only negotiation issue. The limitation of the proposed approach is in its assumption that all agents use the set-and-wait negotiation tactic.

In the case an agent uses the time-dependent tactics, $\lim_{\beta\to\infty}\alpha(t) = (t/t_{max})^{\beta} = 0 \; where \; 0 \leq t < t_{max} \; and \; lim_{\beta\to\infty}\alpha(t) = (t/t_{max})^{\beta} = 1 \; where \; t = t_{max}$, see Equation 2.3. When an agent uses very large β value it offers its initial value at the start of negotiation and waits (set-and-wait strategy) until its deadline approaches and offers its reservation value. The *MCDM* approach assumes that the buyer agent offers a very low price and the seller agents offer a very high price at the beginning of negotiation. Even though the set-and-wait strategy is proven [137] to be the dominant strategy for an agent using a time-dependent strategy regardless of the type of negotiation strategies its negotiation partners may use, this assumption does not fulfill some of the automated negotiation objectives where agents are supposed to exchange multiple offers and counteroffers in order to broaden the search space for possible agreements that suit the negotiating partners. The negotiation strategies proposed in this thesis assume that agents exchange multiple offers and counteroffers during a negotiation encounter.

A coordination model that is based on categorizing the types of the opponent agents into either *conceder* or *non-conceder* are proposed for a buyer agent negotiating concurrently with multiple seller agents. The buyer agent is assumed to have the privilege of making temporary agreements without the need to pay a penalty fee in case it reneges on an agreement(s). In their proposed model, Nguyen and Jennings assume that the buyer agent has a probability distribution about the types of agents (i.e., conceder type and non-conceder type) taken from previous negotiations or from any other party

[106]. If no information is available about the types of seller agents , then all seller agents are considered of unknown type. The model also uses the percentage of success (*PS*) matrix and the pay off (*PO*) matrix. The *PS* records the rate of reaching a successful agreement for each type of the buyer agent's strategies against the two types of seller agents. In other words, the rows of the *PS* matrix consist the buyer's strategies (conceder, linear and tough) and the columns are the conceder and non-conceder seller agent types. The *PO* is similar to the *PS* matrix except it records the utility rate. Equation 2.15 finds the buyers' expected utility of using a certain strategy λ where $\lambda \in \{conceder, linear, tough\}$ which are the only strategies that the buyer uses in the proposed model.

$$EU(\lambda) = \sum_{\mathbb{s} \in A_{types}} PS(\lambda, a)PO(\lambda, a)P(a), \tag{2.15}$$

where $P(a)$ is the probability that the seller agent is of type a. The values $PS(\lambda, a)$ and $PO(\lambda, a)$ are taken from the matrices *PS* and *PO* at the intersection of λ and a. The buyer agent calculates three $EU(.)$ values, one expected utility per a strategy $\lambda \in \{conceder, linear, tough\}$. The buyer agent selects the strategy with the highest expected value. That process is repeated to select a strategy for each negotiation thread. The model uses Bayesian rule to update the probability distribution of the agent types and continues on to select a strategy for the second thread. The experimental results show that the initial information about the probability distribution of the seller types have small positive (1-2 %) results on the buyer's utility rate. Most of the positive experimental results are due to the reclassification process of the seller agent types that the buyer agent performs during negotiation. The buyer agent assigns a certain seller agent into either the A_{con} or the A_{non} sets according to the utility value of its proposals. The buyer agent starts classifying seller agents after receieving the third proposal as follow: at time $t = 3$ and if $\left(\dfrac{U(\mathbb{s}, t) - U(\mathbb{s}, t-1)}{U(\mathbb{s}, t-1) - U(\mathbb{s}, t-2)} > \psi\right)$ then the seller agent $\mathbb{s} \in A_{con}$ otherwise $\mathbb{s} \in A_{non}$ where ψ is the threshold value set on the concessionary behaviour. The buyer applies this procedure in each negotiation round. Equation 2.15 is used to select a strategy λ accordingly. In this case the $P(\mathbb{s})$ can be either 1 or 0.

The proposed model is compared with the desperate, the patient and the optimized patient strategies that were discussed earlier. The experimental results show that the proposed model outperforms the mentioned strategies in terms of the utility rate and agreement rate. However, the model still needs the *PO* and the *PS* matrices for the strategy selection process. In addition, the model limits the buyer's negotiation tactics into only three tactics which is a bit restricting since the number of negotiation tactics can be large. Even though it is mentioned in the experimental section that the number of negotiation issues considered in the experiments can be between 1 and 8, the real impact of having multiple negotiation issues is not clear since the model classifies the seller agents according to the utility of the last 3 offers received from each seller. In addition, the buyer agent uses the time-dependent tactics which -without manipulation- concede on all issues with the same rate in each negotiation round. Moreover, it is not clear how the ψ threshold value can be set and whether it is a fixed value or can be changed during negotiation.

Finally, another study proposes manipulating the convexity of the concession curves of a buyer's agent is presented in [90]. The proposed method uses the current behaviors of the current seller agents to adapt the slop of the buyers' concession curves during negotiation.

2.5.2 One-to-Many Negotiation Over Multiple Issues

In real life, most negotiations involve more than one issue. For example, buying a laptop may involve negotiating the price of the laptop and both, the memory size and processor speed. If the agents participating in negotiation are competitive and self interested, then the objective of each agent is to reach an agreement with the highest possible utility regardless of the opponents' needs or preferences. However, when negotiation involves multiple issues, agents usually have divergent preferences over different issues which allows them to reach an efficient agreement for both parties, i.e., achieving a win-win outcome.

There are a fair number of research papers that discuss negotiation over multiple issues, e.g., [34][37]. However, most works consider bilateral negotiation. For example, Fatima et al. propose a negotiation model for multi-issue negotiation under time constraints in an incomplete information setting [37]. The proposed model allows negotiation over one or more negotiation objects where each object is characterized by a single continuous issue. Moreover, the model investigates the scenario where agents negotiate over a single object characterized by multiple issues. However, the work investigated in [37] focuses on the problem of the agreements' implementation scheme in which the agreements can be implemented either sequentially or simultaneously. The work of this thesis focuses on developing dynamic negotiation strategies that can guarantee effective and/or efficient outcomes for a buyer agent negotiating concurrently with multiple seller agents.

In an interesting study about the one-to-many multi-attribute negotiation setting, Van de Walle et al. [151] consider the problem of evaluating and ranking different offers proposed by a set of buyers. The negotiation setting involves a seller negotiating with multiple buyers over a single object characterized by multiple issues. Given the received offers from the buyers, the objective of the study is on which buyer the seller should focus on to negotiate further and sell its product. A simple strategy to answer such a question is to rank the buyers according to the value of their offers. In this case, the value of each offer is reduced to a single number, i.e., the weighted average utility of the offer. Van de Walle et al. propose an alternative strategy that preserves the information richness of an offer by doing pairwise comparisons of the seller's preference on the buyers' offers and rank the buyers (a partial order ranking) accordingly. The proposed ranking strategy is based on the fact that the preferences over negotiation issues may vary by different negotiating partners. The proposed approach uses the fuzzy sets and fuzzy relations in the pairwise comparison between different issues. In a fuzzy quasi-order relation, each α-cut is a crisp quasi-order relation. Each α-cut of a fuzzy quasi-order relation is a quasi-order relation in the set of buyers. The equivalence relation partitions the buyers into equivalence classes of buyers in which the buyers of each class are of equal quality to the seller agent. The same study also analyzes the sellers' preferences over its different attributes or issues and compares between them at different α-cuts.

The first step in implementing the proposed approach is to construct the *preference relation* matrix. To construct the matrix, the seller needs to assign a value (usually between 0 and 1) to each proposed value for each issue in the received offer of each buyer. For example, if a buyer proposes $\$10$ and 2 days delivery time over a certain item and the preference of the seller is $\$15$ and 2 days delivery time, the seller agent may assign 0.4 to the received price value and 0 to the received delivery time value. It means that the seller does not prefer more than the value of the offered delivery time while the value of the received price is less than its expectation, hence the number corresponds to the received price in the preference relation matrix and is estimated to be 0.4. Building such a matrix is subjective and is not easy to start with. In automated negotiation, the process of constructing the preference relation matrix needs to be repeated each time the seller agent receives a new set of offers. It is not clear how to automate building such matrix during negotiation by an agent. Further more, giving the analyses of buyers' responses and seller's preferences, the study does not show how the seller would choose the level of α-cut. Finally, the proposed work does not explain how to respond to each buyer using the information about buyers' classification.

In another study, Gerding et al. [46] investigate the negotiation scenario where a seller agent is negotiating concurrently with multiple buyer agents for the purpose of selling unlimited amounts of goods such as information. The study proposes a number of one-to-many bargaining strategies for the seller agent that takes into consideration the fairness amongst different buyers. The fairness can be defined from either the seller agent's point of view or from a buyer agent's point of view. Assume that a buyer reaches an agreement at time $t_d \in [t_s, t_s + \Delta]$, d_s is a start time. This agreement is fair relative to a fixed interval $\Delta > 0$ if the seller agent is indifferent amongst all other agreement reached within the interval $[t_s, t_s + \Delta]$. Its definition from a buyer's point of view is related to the notion of envy-free auctions presented in [49]. If a deal reached at $t_d \in [t_s, t_s + \Delta]$ and a buyer does not strictly prefer any other deal reach within the interval $[t_s, t_s + \Delta]$, the deal is considered fair. The proposed idea of assuring fairness is that the seller agent should not accept two simultaneous (or within a predefined slot of time) proposals from two different buyers or more if the proposals differ in their utilities. To be fair amongst buyers, the seller agent should be indifferent to all proposals within a certain slot of time. The action of the seller agent in that case is to propose a counteroffer(s) that ensures equality amongst offers within a certain predefined time interval.

In dynamic and competitive environments, we do not expect buyers to communicate their agreed upon deals given that each buyer agent accepts an agreement according to its own constraints. In addition, the experimental results are based on using an evolutionary algorithm that allows agents to learn from previous negotiations. Again, dynamic agents in dynamic environments may not repeat their behavior patterns which makes using an evolutionary algorithms of little use here.

In another study which also considers a seller agent negotiating with a number of buyer agents for selling bundles of news items where each news item is characterized by negotiation issues: price, quality and content of the delivered goods, Somefun et al. [143] propose an approach where the seller agent uses both, concession strategies and Pareto efficient search strategies during negotiation. The study considers also reaching agreements that are fair to the customers. In their market model, the news items are divided into a number of categories. Within each category, there are two quality of service levels. The first level (low quality) shows the headline news only, while the second one (high quality) offers the complete article. The customer bargains with the seller over the bundle tariff which consists of a fixed part (p_f) and a variable part, p_v. The p_f is the price specified to a bundle with a certain quality of service while the p_f is the price the customer pays for reading a full article whenever the quality of service specifies delivering only the article headline. For each information bundle, agents negotiate over the p_v and p_f. The idea used to achieve a fair agreement with a buyer agent is similar to the idea implemented in [46].

In addition, the study [143] proposes the orthogonal and orthogonal-DF mechanisms as two Pareto efficient search strategies. An agent using the orthogonal strategy finds a counteroffer (at time $t + 1$) that is closest (measured in Euclidean distance) to the last received offer that has the same utility as the one generated at time $t - 1$. The orthogonal-DF adjusts the value of one negotiation issue (e.g., p_v) that was generated by the orthogonal mechanism to speed up the search and its accuracy. Consequently, the p_f also needs to be changed to keep the agent on its current iso-curve. The best results in terms of the distance from the Pareto efficient solution is when a buyer agent uses the orthogonal technique and the seller agent uses the orthogonal-DF technique. If both use the orthogonal-DF, the results are similar to the results when agents use random search. It is obvious that none of the agents have an advantage over the other if both are using the same strategy.

The proposed Pareto efficient search mechanisms are limited to the situation where two continuous issues are used. In addition, it is not clear when the seller agent should move from one iso-curve to another during negotiation. Moreover, the approaches assume that the seller agent decreases its aspiration level by a fixed amount each round. However, the number of existing buyer agents and their behaviors are not considered as a factor that can affect the amount of the next aspiration level!

As a means to approximate a version of qualitative Vickrey auction (*QVA*) that produces a Pareto-efficient outcome where the best seller wins, Hindriks et al. [54] propose using one-to-many negotiation where a buyer agent negotiates with multiple seller agents over an object characterized by multiple issues. The reason behind using the one-to-many negotiation is that at least one negotiation party needs to disclose its preferences and in many cases that option is not accepted by any party due to privacy and trust concerns. Three variants of the alternating protocol are analyzed: 1) the set of allowed offers for all agents is restricted 2) the winning offer is announced after each round 3) the sellers are told whether they have won or not after every round. The results of the experiments show that each of the three mechanisms is able to approximate the efficient outcome defined by the *QVA* [54]. The interesting results of this work indicates that the one-to-many negotiation over multiple issues can reach efficient outcomes that are similar to the one obtained by the *QVA* without the need from any agent to disclose its preferences.

As a dynamic negotiation strategy, a meta-strategy that uses two different offer generation tactics is proposed in [87]. The strategy uses a concession tactic and a trade-off tactic. In each negotiation round, the buyer agent needs to select which tactic type to use depending on the current behaviors of the opponents in terms of their concessions. During negotiation, the buyer agent assigns each seller agent to either a favorable group or unfavorable group. The favorable group offers more concessions than the concessions offered by the corresponding buyer agent's delegates.

2.5.3 One-to-Many Negotiation Over Multiple Distinct Objects

The problem of procuring multiple distinct objects concurrently is a difficult problem due to the possible interdependencies amongst negotiation objects from one side and amongst negotiation issues from the other, see Section 2.4.

As a resource coallocation procurement one-to-many negotiation based model was proposed as a GRID resource management system. In their model, Sim and Shi [138] consider a buyer agent seeking to procure multiple distinct services, each characterized by the price as the only negotiation issue. For each service, the buyer agent conducts multiple negotiations with different sets of service providers, one set for each service. For n types of resources, there would be n sets of service providers. The objective is to reach n agreements, one agreement from each set. The second objective is to maximize the agreements' average utility. If the number of the final agreements is less than n, the negotiation process fails. For each set of the service providers of each service, there is a commitment manager and all the commitment mangers communicate with a coordinator. Each commitment manager is responsible for managing both de-commitments and commitments of temporary deals. The coordinator is responsible to decide whether to accept agreements and quit all negotiations with service providers or to continue in negotiation. A commitment manager finds the probability that a certain seller agent $\mathbb{s}$ reneges on an agreement according to equation 2.16.

$$p^t_{\mathbb{s}_i}[j_l] = \begin{cases} 1 - \dfrac{\sqrt{v(X^t_{\mathbb{s}_i \longrightarrow \mathbb{d}_i}[j_l])}}{max(\sqrt{v(X^t_{\mathbb{s}_i \longrightarrow \mathbb{d}_i}[j_l])}, avg(X^t_{\mathbb{s}_i \longrightarrow \mathbb{d}_i}[j_l]) - x^t_{\mathbb{s}_i \longrightarrow \mathbb{d}_i}[j_l])}, & t < t^{\mathbb{d}}_{max} , \\ 0, & t = t^{\mathbb{d}}_{max} , \end{cases} \tag{2.16}$$

where $p^t_{\mathbb{s}_i}[j_l]$ is the probability (belief) that the seller agent $\mathbb{s}_i$ offering resource R_{j_l} at time t would renege from an agreement. The $X^t_{\mathbb{s}_i \longrightarrow \mathbb{d}_i}[j_l]$ denotes the set of offers sent from the provider of resource R_{j_l} to the buyer agent's delegates $\mathbb{d}_{\mathbb{i}}$ (a delegate is a component in the buyer agent that interacts with one opponent agent, see Section 3.2) at time t, $\sqrt{v(X^t_{\mathbb{s}_i \longrightarrow \mathbb{d}_i}[j_l]}$ is the standard deviation of the set of offers received at time t. Finally, $x^t_{\mathbb{s}_i \longrightarrow \mathbb{d}_i}[j_l]$ is the offer received from the seller agent $\mathbb{s}_i$ for the resource R_{j_l} at time t. When $(avg(X^t_{\mathbb{s}_i \longrightarrow \mathbb{d}_i}[j_l]) - x^t_{\mathbb{s}_i \longrightarrow \mathbb{d}_i}[j_l]) \gg \sqrt{v(X^t_{\mathbb{s}_i \longrightarrow \mathbb{d}_i}[j_l])}$, there is a high probability that the seller $\mathbb{s}_{\mathbb{i}}$ would renege on an agreement since its current offer value is way less than the average of the offers received from all other sellers for the same resource and may find a better deal with other buyer agents. The commitment manager calculates the expected utility of a received offer as follows: $EU(x^t_{\mathbb{s}_i \longrightarrow \mathbb{d}_i}[j_l])) = u(x^t_{\mathbb{s}_i \longrightarrow \mathbb{d}_i}[j_l]) * (1 - p^t_{\mathbb{s}_i})$ where $u(.)$ is a utility function. Each commitment manager uses an approach that is similar to the approach used in [105] to accept a new agreement and/or renege on an existing one. The difference is that [138] uses the expected utility $EU(.)$ to evaluate offers. The $EU(.)$ is communicated to the coordinator.

If there is no intermediate agreement for a resource R_{j_l}, the coordinator predicts the change in utility taking into consideration the maximum predicted utility (u_1) from the proposals at $t+1$ and the maximum utility (u_2) in the acceptable agreements over the resource R_{j_l} at time t. The change in utility is calculated $\Delta u = u_1 - u_2$. If $u_1 < u_2$ then Δu has a negative sign. If the resource has an intermediate agreement then $\Delta u = u(avg(X^t_{\mathbb{s}_i \longrightarrow \mathbb{d}_i}[j_l]) - u(x^{t'}_{\mathbb{s}_i \longrightarrow \mathbb{d}_i}))$ where the $x^{t'}_{\mathbb{s}_i \longrightarrow \mathbb{d}_i}[j_l]$ is the proposal of a temporary deal established at $t', t' \leq t$. For coordinating multiple one-to-many negotiations, the utility-oriented coordination(*UOC*) is proposed. At each negotiation round, the coordinator finds the weighted sum of the expected utility of each resource R_{j_l}. If the weighted utility change is less than zero then the buyer agent finalizes (if possible) all agreements and quits negotiation, otherwise the buyer agent proceeds into the next negotiation round. The interdependencies between different negotiations is manifested since the expected change in the utility of each set of resource providers affect the final decision of accepting the best deals or proceeding in negotiation.

The predicted utility calculations depend on the assumption that the buyer's utility in the consecutive negotiation rounds does not vary significantly [138]. In many cases, that assumption about the change in utility does not hold. For example, if an agent uses the time-dependent tactic to generate offers, then the only situation where the change in an offer's utility in consecutive negotiation rounds remains constant is when the agent shows linear concession behavior, i.e., $\beta = 1$, see Section 3.2. In addition, the number of providers of each resource is not considered in the proposed negotiation model since the buyer agent will be better off when there are a large number of providers for a certain resource. Finally, since all the needed resources in the study [138] have the price as the only negotiation issue, the possibility of shifting money between different resources to help secure a certain resource(s) when it seems difficult for the buyer agent to secure that resource(s) from a certain set of providers is not considered.

A more complex negotiation model that can be used in the cloud market as a trading mechanism is proposed in [135]. The proposed model involves brokers as a middle layer between the consumers and the providers of cloud resources. A buyer agent may conduct concurrent negotiations with several broker agents and a broker agent may conduct multiple negotiations with multiple buyer agents. In addition, the broker agent conducts multiple one-to-many negotiations with multiple resource providers in the cloud market. A broker agent accepts requests for services from buyer agents. A service may consist of multiple cloud resources. The price was the only negotiation issue for all types of resources. A broker agent buys resources and composes a collection of resources to satisfy the buyer agents' need. For the many-to-many negotiations between the buyer agents and the broker agents, a bargaining-position-estimation (*BPE*) strategy is adopted. The *BPE* strategy changes the convexity (by changing the β parameter, see Section 3.2) of the concession curve in the next negotiation round given that the agent uses the time-dependent tactics to generate offers and counteroffers. If an agent changes the convexity of its concession curve, it means it is changing the amount of concession it is going to offer in the next negotiation round. To do that, a buyer agent i uses its bargaining position $B_p^i(t)$ given that $B_p^i(t) = \delta_p^i/\Delta_p^i$, where δ_p^i is the difference between the proposals received from the broker agents at time $t-1$ and at time t. The Δ_p^i is the average value of the difference between the proposals received at the start of negotiation (time $t=0$) and at the proposals received at the current time t. If $B_p^i \gg 1$ then the situation for the buyer is considered favorable because the broker agents are currently offering a larger concession than before. The value of the concession parameter β for the next negotiation period is calculated according to Equation 2.17.

$$\beta^{t+1} = \begin{cases} max(\beta_{min}, \beta^t - (1/\Delta B_p^i)(\beta^t - \beta_{min})), & 1 \leq \beta^t < \infty, \\ \beta^t + (1/\Delta B_p^i), & 0 < \beta^t < 1, \end{cases} \tag{2.17}$$

where $\Delta B_p^i = B_p^i(t) - B_p^i(t-1)$ and β_{min} is the minimum β value which is set before negotiation by an agent i. Depending on the value of ΔB_p^i, an agent can change its stance. For example, if $\beta^t = 3$ which is in the conciliatory region and the current $\Delta B_p^i = 4$ which means the situation for agent i is favorable, $\beta^{t+1} = min(0.1, 3 - (1/4) * (3 - 0.1)) = 0.9$ which means that the agent i stance becomes more tough in terms of concession offering and will offer little concession in the next negotiation round. If $\beta^t = 0.4$ and $\Delta B_p^i = 0.5$ which means the situation for the buyer agent is less favorable, then $\beta^{t+1} = 0.4 + (1/0.5) = 2.4$ which means that agent i becomes conciliatory and will offer more concession in the next negotiation round.

The negotiation outcomes between a broker agent and cloud resource providers affect the broker agent's reservation prices. In each negotiation round, a broker agent calculates the reservation price as the cost of the resource plus a percentage of the resource cost [135]. As a consequence, the utility of the same proposal can vary from a broker agent's point of view from one negotiation round to another.

The proposed multiple one-to-many negotiation approach is similar to the one presented in [138]. The coordination approach includes both, the *UOC* [138] and the regression-based coordination (*RBC*). The difference between them is that the *UOC* predicts the utility of the next proposal while the *RBC* predicts the utility at $t^{'}$ where $t^{'} = (t_{max} - t)/2$, t_{max} is the deadline of the agent adopting the *RBC*. In other words, the broker agent predicts the utility of a proposal at the midpoint between the current time and its deadline. It is selected that way because predicting the behavior of an opponent in the near future may not deliver much information about the long term future and the prediction in the long term future may provide little accuracy. As stated earlier, the problem of using either approach stems from the strict assumption of the opponents' behavior. The linear assumption of the opponents can not hold in many real scenarios. The approach assumes that agents use the time-dependent tactics to generate offers and counteroffers and the convexity of the concession function used is controlled by the value of β. The concession curve is not linear except in case the value of β is around 1. Since the proposed approach considers that agents have limited knowledge about each other, assuming that the behavior of opponent agents is linear, is a great deal of knowledge.

Little work has been done on the scenario where an agent is negotiating for the purpose of procuring multiple distinct objects. The previous work about procuring multiple negotiation objects considers that each object has the price as a single negotiation issue. In addition, the coordination mechanism objective is to decide whether to accept the best available deals or to proceed with negotiation. The work in this thesis considers coordinating multiple concurrent negotiations from a different angle. The problem of resource distribution over common negotiation issues during negotiation is considered. For example, if a buyer agent needs to procure three distinct objects (e.g., a camera, a phone and a laptop) given that the criteria (such as the color of the phone must be black) of each object is predefined and the only issue under negotiation is the price, then during negotiation, the buyer agent can estimate the difficulty of procuring each object from evaluating the proposals received for the object and then allocating a reserve price for each object accordingly. That reserve price can change in each negotiation round depending on the current bargaining power of the buyer agent. The same idea can apply in case agents negotiating over objects characterized by multiple issues.

The works in [89] [91] [88] investigate the scenario where a buyer agent seeks agreements over multiple objects given that each object has several issues and a single provider. The proposed approaches in [89] [91] depend on allocating the available resources to the common issues of different objects dynamically during negotiation. The works presented in [89] [91] investigate the process of adapting the local reservation (see Section 4.3) values during negotiation according to the behaviors of the existing opponents over the common issues. Each common issue is assigned (possibly) a new local reservation value in every negotiation round. The work in [88] involves the adaptation of both, the initially generated counteroffers and the issues' counteroffers weight matrix during negotiation. Instead of adapting the local reservation values, the approach presented in [88] adapts a matrix that determines how much each delegate should propose for each issue of each object at the start of every negotiation round. In addition, Chapter 7 investigates a more complex negotiation scenario where the objective of the buyer agent is to procure multiple distinct objects where each object is characterized by multiple issues and have multiple providers.

2.6 Summary

This chapter first introduces the multiagent systems and their potential application domains including automated negotiation. The automated negotiation is introduced in Section 2.2. The section highlights the importance of negotiation as a conflict resolution mechanism and the most important research areas that are related to automated negotiation. In addition, it discusses the pros and cons of adopting the concurrent negotiation approach. Moreover, the potential application domains of automated negotiation are presented.

Section 2.3 introduces the main approaches to negotiation including the game-theoretic approaches, the learning and reasoning approaches and the argument-based ones. In addition, the heuristic-based approaches including the time-dependent, the behavior-dependent and the mixed tactics are discussed. The advantages and disadvantages of each of the mentioned approaches are discussed in terms of their practical application and feasibility including their computational power and processing time needs. The game-theoretic approaches have their limitations in their hard assumptions about the kind of knowledge they require and the unbounded rationality of agents. The learning and reasoning approaches require historical data and/or large amounts of computational and time resources. The argument-based mechanisms have a future potential in facilitating negotiating complex matters but is still in its early stages. The heuristic negotiation approaches are simple and more practical than the other approaches, especially in the research oriented studies.

The dependencies and coordination where the sources of dependencies in the context of negotiation are discussed in Section 2.4. This part defines the possible interdependencies amongst the objects of negotiation such as the objects' procuring order and the possible interdependencies amongst the issues of negotiation such as when a group of issues share a resource such as money.

The last section is the coordination and negotiation section. It presents a short introduction to the coordination mechanisms that are used in multiagent systems and shows how negotiation is considered as one of these mechanisms. It also emphasizes that the aim of this thesis is to coordinate the concurrent multi-bilateral negotiations. In addition, the relevant related works on the one-to-many negotiation focusing on the different coordination mechanisms proposed in the literature are presented.

Most of the one-to-many negotiations in the literature investigate the situation where an agent seeks to procure a single object characterized by a single issue. Managing the convexity of the concession curves and/or updating the reservation values during negotiation are amongst the coordination techniques that are adopted in the related work as well as in this thesis. When the negotiation scenarios involve a single object of a single negotiation issue, novel coordination mechanisms that are based on managing the convexity of the concession curves are proposed and benchmarked against the proposed mechanisms in the literature.

In the related work, previous negotiation data (e.g., utility rates) or some knowledge about the probability distribution of some key data (e.g., the reservation values of the opponents) are used to coordinate different negotiations. The negotiation mechanisms proposed for a buyer agent in this thesis use only the negotiation information in the current negotiation, i.e., the values of the received offers in the current negotiation encounter. On the other hand, the case where agents negotiate multiple objects are rarely addressed in the negotiation literature. The works presented here address the negotiation scenarios where a buyer agent negotiates with multiple seller agents over multiple objects, e.g., services. Other related works propose the decommitment management approach as a coordination mechanism where an agent is allowed to renege from a previous agreement(s) by paying a penalty. The decommitment management approach is not investigated in this thesis since the types of agreements considered are either binding for the agents or such that the buyer agent has the privilege of reneging from an agreement without paying penalty.

Chapter 3

General Negotiation Model

This chapter presents a novel negotiation model that captures various negotiation scenarios. The model emphasizes that the negotiation object is one of the main components that are necessary for describing any negotiation scenario. The model defines negotiation thread, negotiation instance, connected agreement and disconnected agreement. It also introduces the term delegate for describing an agent's component that can negotiate with other agents on the behalf of the agent. In this case, the agent can create and destroy any number of delegates during negotiation as needed. The utility functions that are used to evaluate offers are also presented. Finally, since an object can have one or more negotiation issues, an agent needs to decide when to accept an offer, the offers' evaluation decisions are discussed.

3.1 Introduction

The negotiation model is an important tool for describing any negotiation scenario. A negotiation scenario in multiagent systems contains agents as the interacting components. Agents need to have common interests over a certain object(s) which serve as the purpose of interaction between them. In addition, agents need to know the things that they need to negotiate which are represented as negotiation issues. Each negotiation issue has constraints in which the agent cannot go beyond during negotiation. In addition, agents need to follow a certain interaction rule. Moreover, the agents need to be aware about the policy of accepting an agreement in different circumstances.

3.2 Overview of the Negotiation Model

The first part of this section presents the negotiation model in terms of its main components: agents, negotiation objects and negotiation issues. In addition, it presents how these components interrelate and the main assumptions of this of thesis. The second part discusses how agents evaluate offers and counteroffers especially when negotiating multiple issues.

3.2.1 Negotiation Model

The following formalized negotiation model is general and can be used to describe various negotiation scenarios. The negotiation is presented by the tuple $\mathcal{N} =< \mathbf{O}, \mathbf{S}, \mathbf{D}, \mathbf{J} >$ where,

1. **O** is the set of negotiation objects where agents have interest to negotiate over. A negotiation object represents either a physical item (e.g., a printed book, a camera etc.) or a non-physical item, e.g., a service, a resource etc. The set of objects $\mathbf{O} = \{o_1, ..., o_m\}$, where o_i stands for a negotiation object. It is assumed that the **O** set contains all the negotiation objects and remains unchanged throughout negotiation.

2. **S** is the set of seller agents in the current negotiation encounter, $\mathbf{S} = \{s_1, ..., s_m\}$. If one or more negotiation objects have more than one provider, then $s_i = \{s_{i1}, ..., s_{in_i}\}$ where i is the object identity in which the group s_i is aiming to sell and n_i is the number of seller agents that are willing to sell object o_i, see Figure 3.1, otherwise, s_i stands for a seller agent who is willing to sell the object o_i, see Figure 3.2.

3. **D** is the set of buyer agent's negotiation *delegates*, $\mathbf{D} = \{d_1, ..., d_m\}$. If one or more negotiation objects have more than one provider, then d_i represents a set of delegates, $d_i = \{d_{i1}, ..., d_{in_i}\}$, that are responsible for buying object o_i where i is the object identity, n_i is the number of the buyer agent's delegates responsible for buying object o_i, see Figure 3.1. If object o_i has one provider, then d_i stands for a buyer's delegate who is responsible for buying object o_i, see Figure 3.2.

4. **J** is the set of negotiation issues or attributes, $\mathbf{J} = \{j_1, ..., j_g\}$, where j_i is an issue characterizing at least one negotiation object.

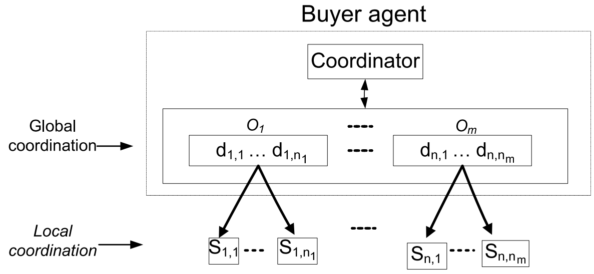


Figure 3.1: *Complex one-to-many negotiation*

In addition to the notation described above, the following assumptions are considered in this thesis:

- $|D| = |S|$. It means the number of delegates are equal to the number of seller agents at any point of time during negotiation. The delegates are created and destroyed during negotiation to match the number of seller agents.
- $\forall s_i \in S$ and $\forall d_i \in D, |d_i| = |s_i|$. It is similar to the previous point and applies in case an object has multiple providers.
- $\forall o_i \in \mathbf{O}$, $o_i \sim J_q$ where $J_q \in 2^{\mathbf{J}}$. It means that each object is characterized by a set of issues. It is possible that two or more objects have the same set of issues.
- agents use the *alternating offers protocol* [125].
- in case of multi-issue negotiation, when an agent reaches an agreement over a negotiation object, it means that the agent have an agreement over each issue of that object using the *object response* and the *issue response* decision making mechanisms, see Section 3.2.2
- each negotiating agent has a deadline by which the agent accepts an offer or withdraws from negotiation.
- agents negotiate under incomplete knowledge, since the reservations values, deadlines, utility structure and the offer generation models are private information.

- we assume that the seller agents are independent in their actions, i.e., they do not exchange information.
- sometimes, we refer to a buyer agent's delegate as an *agent* since it takes the responsibility of receiving offers and sending counteroffers to a seller agent.
- negotiation agents are rational agents, see Section 2.1.
- negotiations are assumed to be one-off. In this case, the information about the previous negotiation encounters are not considered.
- agents negotiate in an open and dynamic environment, as a result, the agent's reputation matter is not considered in this work.
- all agents are equal in their capabilities and can do the same set of actions.
- even though we represent the negotiation model from a buyer agent's point of view, the model is general can be used to represent a seller agent's point of view as well.

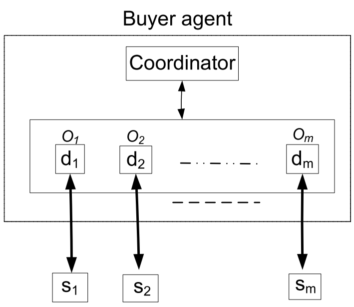


Figure 3.2: *One-to-many negotiation*

When a buyer agent seeks to reach agreements over multiple objects, the agreements over the objects can be either *connected agreement* or *disconnected agreement*.

Definition 3.1. *(***Connected agreement***)*

In multi-object negotiation, a connected agreement is an agreement under the condition that an agent is required to reach an agreement over each negotiation object. If the number of negotiation objects is m, then the agent needs to secure m agreements to count for one successful agreement. In other words, if an agent fails to reach an *agreement over any negotiation object then the negotiation ends with a conflict deal and the utility for that agent is assumed to be zero.*

Similarly, an object agreement is considered a connected issue agreement since an agent must reach an agreement over every issue.

Definition 3.2. *(***Disconnected agreement***)*

In multi-object negotiation, if an agreement over each negotiation object is not a strict obligation, then an agreement over any object is considered a disconnected agreement. One disconnected agreement counts for one agreement. An agent counts how many disconnected agreements are achieved in a negotiation encounter for the purposes of evaluating the negotiation process.

In case the agreements are of a disconnected type, an agent seeks to reach the largest possible number of agreements and the overall utility of the final agreement is calculated by considering only the utilities of the objects in which the agent reaches agreements over.

We assume that each negotiation delegate is responsible to negotiate over one object at a given negotiation encounter (see function f_d in Equation 3.1), while many delegates may negotiate with many seller agents over the same object concurrently.

The negotiation scenario described in Figure 3.1 is a bit complicated since the coordinator unit in the buyer agent needs to consider two levels of coordination, one at the level of each object (i.e., local level) and another at the level of all objects, i.e., global level.

In our model, each negotiation delegate is mapped to an object, a deadline $t_{max} \in \mathbb{N}^*$, an offer generation strategy $\theta \in \Theta$, and an object weight $W_i \in (0, 1]$, see f_d in Equation 3.1. The objects' weights are used to calculate the weighted average utility of procuring m objects under the assumption that the objects are independent and $\sum_{i=1}^{m} W_i = 1$.

$$
\begin{aligned}
&f_d : \mathbf{D} \xrightarrow{1-1} (\mathbf{O} \times \mathbb{N}^* \times \Theta \times W_i \times ...) \\
&f_o : \mathbf{O} \xrightarrow{1-1} 2^{\mathbf{J}} \\
&f_j : \mathbf{J} \xrightarrow{1-1} ([min, max] \times ...)
\end{aligned}
\tag{3.1}
$$

Each object is mapped to a negotiation issue set J_q where $J_q \in 2^{\mathbf{J}}$, see f_o in Equation 3.1. Finally, each issue is mapped to a set of constraints, e.g., the interval of acceptance ($[min, max]$), where min,max represent either the starting offer value or the reservation value of a negotiation issue, see f_j in Equation 3.1. When min is the starting offer value then max is the reservation offer value and vice versa. Usually, a seller agent starts proposing a high price (i.e., its *max*) for a certain item, then it may concede up to its minimal acceptable price for this item, i.e., its *min*. The buyer agent behaves the opposite way regarding the price issue.

In each negotiation round, the buyer agent may need to execute one or more of the three functions (i.e., f_d, f_o, f_j in Equation 3.1) as a response to some changes in the negotiation environment, such as destroying a delegate as a result of withdrawing its partner seller agent from negotiation or reaching an agreement over the object assigned to that delegate, changing or updating the current negotiation tactic etc. The buyer agent creates and destroys delegate negotiators during negotiation to match the number of the existing seller agents.

We use the notation $x^t_{\mathbb{d}\to\mathbb{s}}[J_q]$ to stand for the vector of values proposed by an agent $\mathbb{d}$ to an agent $\mathbb{s}$ ($\mathbb{s} \in \{s_i, s_{il}\}$ and $\mathbb{d} \in \{d_i, d_{il}\}$) at time t given that the $x^t_{\mathbb{d}\to\mathbb{s}}[J_q]$ has a value for each issue $j_l \in J_q$ and $\exists\ o_i \sim J_q$. All the formulae included in this chapter can be used by both agent types, i.e., $\mathbb{d}$ and $\mathbb{s}$. To refer to a value of a certain issue say $[j_l] \in x^t_{\mathbb{d}\to\mathbb{s}}[J_q]$, we use the notation $x^t_{\mathbb{d}\to\mathbb{s}}[j_l]$. Assume that agents are negotiating over independent issues, let $U^{\mathbb{b}}(x^t_{\mathbb{s}\to\mathbb{d}}[J_q])$ be a function that computes the weighted average utility of the agent $\mathbb{d}$ from receiving the offer $x^t_{\mathbb{s}\to\mathbb{d}}[J_q]$ at time t. The weighted average utility of delegate $\mathbb{d}$ is computed according to Equation 3.2.

$$U^{\mathbb{d}}(x^t_{\mathbb{s}\to\mathbb{d}}[J_q]) = \sum_{l=1}^{|J_q|} \mathcal{W}_l * u^{\mathbb{d}}(x^t_{\mathbb{s}\to\mathbb{d}}[j_l]), \tag{3.2}$$

where $\sum_{l=1}^{|J_q|} \mathcal{W}_l = 1$ and $u^{\mathbb{d}}(x^t_{\mathbb{s}\to\mathbb{d}}[j_l])$ is a function that calculates the utility gain of the agent $\mathbb{d}$ from receiving the offer $(x^t_{\mathbb{s}\to\mathbb{d}}[j_l])$, see Equation 3.3 below. For m objects, the agent computes m utility values. The total utility is calculated as the average of m utility values given that all objects have the same importance (i.e., the same weight) to the buyer agent. In case objects differ in their importance, the total utility is calculated as a weighted average of m utility values given that the objects under negotiation are independent.

An agent uses equation 3.3 to compute the utility of a single issue offer. For example, a buyer's delegate $\mathbb{d}$ uses the utility function $u^{\mathbb{d}}$ to evaluate an offer received from an agent $\mathbb{s}$ over an issue j_l:

$$u^{\mathbb{d}}(x_{\mathbb{s}\to\mathbb{d}}[j_l]) = \begin{cases} (x_{\mathbb{s}\to\mathbb{d}}[j_l] - RV^{\mathbb{d}}_{j_l})/(IV^{\mathbb{d}}_{j_l} - RV^{\mathbb{d}}_{j_l}), & If(IV^{\mathbb{d}}_{j_l} > RV^{\mathbb{d}}_{j_l}) \\ (RV^{\mathbb{d}}_{j_l} - x_{\mathbb{s}\to\mathbb{d}}[j_l])/(RV^{\mathbb{d}}_{j_l} - IV^{\mathbb{d}}_{j_l}), & If(IV^{\mathbb{d}}_{j_l} < RV^{\mathbb{d}}_{j_l}) \end{cases} \tag{3.3}$$

The buyer agent uses Equation 3.3 to evaluate both, the received offer over an issue and its generated counteroffer over that issue. Similarly, with simple modifications, Equations 3.2 and 3.3 can be used by the seller agents for the purpose of calculating the weighted average utility and the single issue offer utility, respectively, for the counteroffers they receive and the offers they generate.

The set of offers and counteroffers that are exchanged between any negotiation pair during the current negotiation encounter is called a *negotiation thread*. Formally, the negotiation thread denoted by $X^t_{\mathbb{d}\leftrightarrow\mathbb{s}}[J_q]$ is defined as follows:

Definition 3.3. *(***Negotiation thread***)*

Assuming that a seller agent $\mathbb{s}$ *starts proposing at time* $t = 0$*, the negotiation thread for the negotiation pair* $(\mathbb{d}, \mathbb{s})$ *over an object* $o_i \sim J_q$ *at time* t *is denoted by* $X^t_{\mathbb{d}\leftrightarrow\mathbb{s}}[J_q]$*, where* $X^t_{\mathbb{d}\leftrightarrow\mathbb{s}}[J_q] =< x^t_{\mathbb{d}\to\mathbb{s}}[J_q], x^{t-1}_{\mathbb{s}\to\mathbb{d}}[J_q], x^{t-2}_{\mathbb{d}\to\mathbb{s}}[J_q], ..., x^0_{\mathbb{s}\to\mathbb{d}}[J_q] >$ *. The first element is optionally* $\in$ *{accept,withdraw}. A negotiation thread* $X^t_{\mathbb{d}\leftrightarrow\mathbb{s}}[J_q]$ *is active at time* t *if* **first***(*$X^t_{\mathbb{s}\leftrightarrow\mathbb{d}}[J_q]) \notin \{accept, withdraw\}$ *where* **first(.)** *is a function that returns the first element in a sequence.*

The above definition is adapted from [33]. In general, the negotiation thread is considered the real-time information that is available for a negotiating agent. It can be used in the process of decision making regarding the required action(s) in the next negotiation round, e.g., withdraw from negotiation, what the value of the next offer is etc. The decision making mechanisms proposed in this thesis rely on the active *negotiation threads* as the source of real-time information. The negotiation threads can be used to analyze the different patterns of concessions offered by different opponents in the one-to-many negotiation.

To refer to a negotiation interaction between a buyer's delegate and a seller agent, the term *negotiation instance* is used.

Definition 3.4. *(***Negotiation instance***)*

A negotiation instance describes an active negotiation interaction between two agents. The number of negotiation instances at a given time is equal to the number of active negotiation pairs.

A negotiation instance is similar to a negotiation encounter. The difference is that the *negotiation instance* describes an active negotiation encounter. In the one-to-many negotiation, a negotiation instance is used to describe a negotiation encounter between a buyer's delegate and a seller agent. When the buyer agent creates a new delegate, it actually creates a new instance which is a term borrowed from the object oriented paradigm. Moreover, the negotiation encounter term is connected more to bilateral negotiation.

The number of *negotiation instances* is dynamic in the one-to-many negotiation. For example, when an agreement is reached between a delegate and a seller agent, the number of negotiation instances is reduced by one and if a new seller agent engages in negotiation, the number of negotiation instances is increased by one etc. In the one-to-many negotiation, the number of active negotiation threads is equal to the number of negotiation instances at any given time during negotiation.

3.2.2 Evaluation Decisions

When a buyer agent's delegate $\mathbb{d}$ receives an offer for an issue j_l from its opponent seller agent $\mathbb{s}$, it needs to evaluate the received offer using its utility function. If the utility function does not exist, other evaluation criteria can be used such as existing of *minimum constraints* accepting criteria or using certain *ranking ordering rule*. The minimum constraints means that the agent accepts any offer that matches or exceeds its minimal constraints. On the other hand, the rank ordering rule works when an agent is able to rank its preferences over the decision variables and if the received offer is aligned with this ranking, the offer is accepted. In this thesis, a utility function is used in the evaluation process. In case of existing multiple negotiation issues and/or multiple negotiation objects, the negotiation decision mechanism needs to accommodate for the existing multiple decision variables. In case an object has multiple issues and issues are different in their importance, the utility of the object's offer is calculated as a weighted average utility. Similar procedure is applied in case of existing multiple objects. The difference is that the objects can also have different weights if they differ in their importance from an agent's point of view. When the negotiation objects have different weights, the utility of each object is calculated as a weighted average utility and the utilities of all objects are calculated again as a weighted average utility using the objects' weights instead of issues' weights. The following definitions formalize the evaluation decisions in different situations.

Definition 3.5. *(***Issue response I(.)***)*

At the start of each negotiation round, an agent $\mathbb{d}$ *takes an* **issue response I(.)** *decision at time* $t^{'}$ *regarding the received offer (*$x^{t}_{\mathbb{s}\to\mathbb{d}}[j_l]$*) given that* $t < t^{'}$ *as follows:*

$$\mathbf{I}^{\mathbb{d}}(t^{'}, x^{t}_{\mathbb{s}\to\mathbb{d}}[j_l]) = \begin{cases} accept & if(u^{\mathbb{d}}(x^{t}_{\mathbb{s}\to\mathbb{d}}[j_l]) \geq u^{\mathbb{d}}(x^{t^{'}}_{\mathbb{d}\to\mathbb{s}}[j_l])\ \&(t^{'} \leq t^{\mathbb{d}}_{max})) \\ withdraw & if(t^{'} > t^{\mathbb{d}}_{max}) \\ send(x_{\mathbb{d}\to\mathbb{s}}[j_l]) & otherwise \end{cases} \tag{3.4}$$

The *issue response* ($\mathbf{I}^{\mathbb{d}}$) considers the utility of the received offer by delegate $\mathbb{d}$ for an object o_i represented by the issue j_l. The *issue response* in Equation 3.4 applies in case agents are negotiating over a single issue. To handle the situation of multiple-issue negotiation, Equation 3.5 is applied to each element of the composite offer to make sure that the utility of each issue is not less than the utility of the reservation value of that issue. Equation 3.5 is applied after the *conditional accept* decision is selected in the *object response*, see Equation 3.6.

$$\widetilde{\mathbf{I}}^{\mathbb{d}}(t^{'}, x^{t}_{\mathbb{s}\to\mathbb{d}}[j_l]) = \begin{cases} accept & if(u^{\mathbb{d}}(x^{t}_{\mathbb{s}\to\mathbb{d}}[j_l]) \geq u^{\mathbb{d}}(RV^{\mathbb{d}}_{j_l})) \\ reject & if(u^{\mathbb{d}}(x^{t}_{\mathbb{s}\to\mathbb{d}}[j_l]) < u^{\mathbb{d}}(RV^{\mathbb{d}}_{j_l})) \\ withdraw & \quad if(t^{'} > t^{\mathbb{d}}_{max}) \end{cases} \tag{3.5}$$

The modification of the offer acceptance condition in Equation 3.5 is connected to the *object response* $B^{\mathbb{d}}(.)$ since the object response is concerned with the weighted average utility of the received composite offer. Equation 3.5 does not have the *send(.)*

option since it is used only to check whether the utility of each issue's offer of the received composite offer that has the status *conditional accept* does not go beyond the reservation utility of that issue, i.e., the minimum acceptable utility.

The *accept* and *reject* in Equation 3.5 are two labels that can be used to mark the status of each issue. If the utility of a certain issue member of a received composite offer is equal to or above the reservation utility of that issue, then the status of that issue will be "accept", otherwise, the status is "reject".

Definition 3.6. *(***Object response B(.)***)*

At the start of each negotiation round, an agent $\mathbb{d}$ *takes an* **object response B(.)** *decision at time* $t^{'}$ *regarding the received offer (*$x^{t}_{\mathbb{s}\to\mathbb{d}}[J_q]$*) given that* $t < t^{'}$ *as follows:*

$$\mathbf{B}^{\mathbb{d}}(t^{'}, x^{t}_{\mathbb{s}\to\mathbb{d}}[J_q]) = \begin{cases} conditional\ accept\ \ if(U^{\mathbb{d}}(x^{t}_{\mathbb{s}\to\mathbb{d}}[J_q]) \geq U^{\mathbb{d}}(x^{t^{'}}_{\mathbb{d}\to\mathbb{s}}[J_q])\ \&(t^{'} \leq t^{\mathbb{d}}_{max})) \\ withdraw \qquad\quad if(t^{'} > t^{\mathbb{d}}_{max}) \\ send(x_{\mathbb{d}\to\mathbb{s}}) \qquad otherwise \end{cases} \tag{3.6}$$

The *object response* ($\mathbf{B}^{\mathbb{d}}$) considers the weighted average utility of the received offer by delegate $\mathbb{d}$ for an object o_i represented by the set of issues J_q.

If an agent $\mathbb{d}$ decides to conditionally accept an offer according to $\mathbf{B}^{\mathbb{d}}$, then it needs to apply the *issue response* ($\widetilde{\mathbf{I}}^{\mathbb{d}}$) criteria shown in Equation 3.5 on each issue to make sure that no issue receives a lower utility than its reservation utility. Because it is possible that the weighted average utility of a certain composite offer is acceptable due to the utility of a member offer (or more) is high whereas the utility of other member(s) of the composite offer is/are under its/their reservation utility. In other words, the decision of accepting a composite offer includes two steps, first, check the weighted average utility of the received composite offer for a certain object and then check the individual utility of each member of that offer. If the first result is true and the second result is true for each member of the composite offer then the offer is accepted. Figure 3.3 shows the decision process of accepting a multi-issue offer.

The other way around of making decisions over whether to accept a certain composite offer is also possible. The agent starts inspecting the utility of each member of the received composite offer and if all utilities are acceptable, the weighted average utility

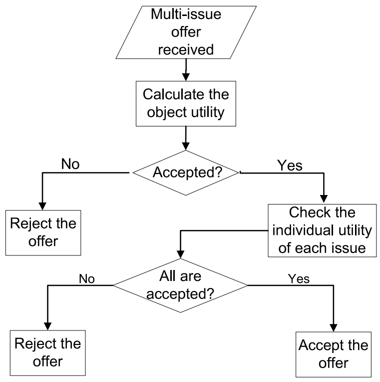


Figure 3.3: *The decision process of accepting a multi-issue offer*

is computed and compared against the current aspirational level of the agent. If it is equal or above that level, the offer is accepted, otherwise the offer is rejected. During the process of computing the utility of the individual members of the composite offer, it is possible that the utility of a member is the less than the current required utility level of that issue. In this case, the process stops and the composite offer is rejected. However, when using the *object response* method, an agent computes the weighted average utility of the composite offer first and marks the received composite offer with the *conditional accept* label if its utility is equal or more than the current aspiration level. The next step is to apply the $\widetilde{\mathbf{I}}$. If any issue member of the composite offer receives the label *reject* from $\widetilde{\mathbf{I}}$, the agent's behavior in the next negotiation round can be aligned towards reaching an agreement over the issues who receive the label *reject* by the $\widetilde{\mathbf{I}}$. The agent may offer more concession on the issue(s) marked with the *reject* label to increase the opportunity of changing the labels of those issues from *reject* to *accept*. However, the agent needs to repeat the decision process of accepting a multi-issue offer in every negotiation round. The offer acceptance decision making mechanisms described above are applied by the buyer agents and the seller agents.

3.3 Summary

This chapter presents a novel negotiation model that captures various negotiation scenarios. It describes the negotiation as a tuple of 4 vectors: objects, sellers, delegates and issues. The objects are the items which agents have interest to negotiate over. An object is characterized by one or more issues and every issue has a set of constraints.

Each delegate can negotiate with one seller agent over one object. In other words, a delegate can be responsible for procuring only one object in any given interaction. The proposed notation allows for the description of the situations where there is a single provider per object and when an object can have multiple providers. The first case has a single level of coordination, while the second case can have two levels of coordination.

The buyer agent creates a number of delegates equal to the number of seller agents that are still in negotiation. If a seller agent quits negotiation or an agreement is reached with a certain seller agent, its delegate partner is destroyed. Each delegate is assigned an object and each object is assigned a set of issues. Finally, each issue is assigned a set of constraints. The two main issue constraints that are used in this thesis are: the issue reservation intervals and the issue weights vector.

The utility function that are used to evaluate offers and counteroffers are presented. The utility function uses the minimum and the maximum values of the reservation interval of a given issue to calculate the utility value for a received or generated offer for this issue. The utility value can be any number in the closed interval $[0, 1]$. In addition, the weighted average utility is explained. The agents use the alternating offers protocol during their interaction.

The model also defines some relevant terms: negotiation thread, negotiation instance, connected agreement and disconnected agreement. Finally, the model discusses the evaluation decisions for the offers. Additional terms such as issue response and object response mechanisms are proposed, defined and discussed. These mechanisms are used in the offer accepting process.

Chapter 4

Coordination Scenarios and Solution Approach

This chapter introduces the coordination problem in the concurrent multi-bilateral negotiation and emphasizes the coordination direction of this thesis. Possible negotiation scenarios in multiagent systems are classified. The classification includes the bilateral (i.e., one-to-one) negotiation and the multi-bilateral (i.e., one-to-many) negotiation whereas the many-to-many negotiation can be formed by either. Five scenarios in the one-to-many negotiation are identified and named coordination scenarios. Moreover, the general solution approach is presented including a detailed example about the data preparation. Finally, the general experimental settings are presented.

4.1 Coordination Problem in One-to-Many Negotiation

Consider a reverse auction where a buyer agent interacts with multiple seller agents. Instead of adopting the reverse auction rules of encounter amongst agents, the alternating offer protocol are assumed as a rule of the encounter. The buyer agent receives multiple offers from the seller agents at time t and it responds at time $t + 1$. In reality, the responses of the seller agents may not be synchronized in terms of the time of their response, however, for simplicity, all seller agents are assumed to send their offers at the same time and the buyer sends its counteroffers to all seller agents at once. Each agent has a deadline by which it either accepts an offer or withdraws from negotiation.

Unlike the reverse auction where the price is the only issue of interest for all agents, we consider the situation where the agents are interested in negotiating over not only a single issue, but over multiple issues such as delivery time, response, time etc.

When the buyer agent receives multiple offers at time t where $t < t_{max}^{buyer}$, the buyer agent can take one of two decisions: accept one or more of the received offers and quit negotiation or reject some or all of the received offers and propose one or more counteroffers. Some negotiation protocols allow the buyer agent to accept offers temporary while in negotiation. As stated in Section 2.5.1, this thesis does not consider the problem of managing commitment/decommitment. The investigated cases are when the buyer agent can renege on an agreement(s) without the need to pay penalty or it needs to honor its agreement(s).

Certain mechanisms are proposed in the negotiation literature to coordinate the concurrent one-to-many negotiation. Most of the work focuses on tackling the following two main coordination problems:

- *the proposal accepting* problem. Some coordination mechanisms (e.g., [138] [3] [23]) are designed to answer the following question: when an agent receives a number of offers in a certain negotiation round, should the agent accept the best acceptable offer and quit negotiation? In this case the coordination mechanism should consider different factors such as the value of the best existing offer, the number of existing opponents, the agents' deadlines and the expected utility of the opponents' future offers. The proposal accepting problem exists in all forms of negotiation. Since deadlines and preference profiles are considered private information of each agent, it becomes difficult for an agent to decide whether to agree on an acceptable agreement or proceed with negotiation. If the buyer agent accepts the best acceptable offer, it may lose a higher future offer value. On the other hand, if the agent decides to continue in negotiation, it may not reach an agreement at all since the deadlines of the opponent agents are private information and the opponent agents may withdraw from negotiation at any time. If an agent reaches its deadline during negotiation, i.e., current time $t = t_{max}$, the dominant strategy for an agent is to accept the best acceptable offer. If $t < t_{max}$ then it becomes difficult to determine the dominant strategy. In case an agent decides to proceed in negotiation, the risk of not reaching an agreement in case of bilateral negotiation is higher than the case of multi-bilateral negotiation. In multi-bilateral negotiation, an agent negotiates with multiple opponent agents concurrently and the probability that all agents withdraw from negotiation at once is less than the probability of a single agent withdrawing from negotiation.

- *the bidding strategy* problem. This problem tackles the problem of generating offers (e.g., [118][18][40][34] [24]) for the next negotiation round. It can involve defining either the offer value and/or the offer structure. Different methods are proposed to generate offers such as using mathematical functions that depend on the elapsed negotiation time and the value of the convexity parameter, imitation offer generation mechanisms and mixing techniques, see Section 2.3.3. Other methods are designed to propose trade-off offers to help reach an agreement faster and at the same time do not jeopardize the utility of the proposer agent, see Section 2.3.3.5. Even though manipulating the offer structure during negotiation may help in reaching an agreement(s), its automation process is rarely addressed in the negotiation literature.

The *bidding strategy* problem is an important problem in negotiation and in all negotiation forms. It is a more challenging problem in the one-to-many negotiation since the buyer agent needs to consider the behaviors of a number of opponents and a different offer may need to be proposed to each opponent. Most of the work in this thesis focuses on the bidding strategy in one-to-many negotiation. The focus is on devising dynamic bidding strategies that consider the collective behaviors of the opponents in terms of the their concession. The buyer agent uses only the received offers in the current negotiation instance as source of data in the proposed dynamic bidding strategies.

The main coordination problem presented in this thesis is the problem of managing the interdependencies between the generated counteroffers by a buyer agent negotiating concurrently with a set of seller agents taking into consideration the behavior of each seller agent. The interdependencies are managed by detecting the behaviors of the opponent agents in terms of their concession behavior over different negotiation issues in each negotiation round. The process is repeated in each negotiation round since the seller agents may change their behaviors from one negotiation round to another.

The main coordination question addressed by this thesis is:

> *Given the offers received by a buyer agent from the seller agents and the counteroffers sent to the seller agents in the current negotiation instance, what is the value of the next counteroffer that a buyer agent should send to each seller agent?*

The values of the next counteroffers are decided by the buyer's bidding strategy. Coordinating the buyer's actions in that context means coordinating the buyer's bidding strategy during negotiation. For the rest of this thesis, the term *offer* is used to refer to a proposal generated by *an agent* or *a seller agent* while a *counteroffer* refers to a proposal generated by *a buyer agent*. *An agent* in this context can be either a buyer or a seller agent.

The coordination objective is twofold: firstly, the buyer agent needs to secure an agreement(s) beyond its reservation value(s), secondly, the coordination mechanism(s) needs to be designed in a way that maximizes the utility of the agreement(s). In other words, the coordination mechanisms maximize the utility of the agreements, see Equation 4.1.

$$maximize\left(\frac{\sum_{i=1}^{m}\sum_{l=1}^{|g_i|} u(x[j_l])}{m}\right), \tag{4.1}$$

where m is the number of objects under negotiation, g_i is the issue set of the object i and $u(x[j_l])$ is the utility of the accepted value for the issue j_l. The utility function is discussed in Section 3.2. Equation 4.1 assumes that all objects under negotiation have the same weight or importance. If the objects have different importance, Equation 4.1 needs to reflect that.

The next section presents the classification of negotiation and coordination scenarios while Section 4.3 elaborates more on the coordination problem and presents the general solution approach.

4.2 Coordination Scenarios

This section categorizes possible negotiation scenarios (adapted from the work published in [86]) in multiagent systems taking into consideration the two main criteria of a negotiation object that determine a particular negotiation scenario: the *number of negotiation issues* and the *number of opponents (providers) per object at a given negotiation interaction*. In addition, the *number of the required agreements* are added to indicate the number of the required objects, see Figure 4.1. We consider that each *negotiation object* requires one *object agreement* and each issue requires one *issue agreement*. Formally, if an object o_i has k issues, then we need k *issue agreements* to make an *object agreement* over the object o_i. For the rest of this manuscript, unless stated to the contrary, an agreement means an agreement over an object.

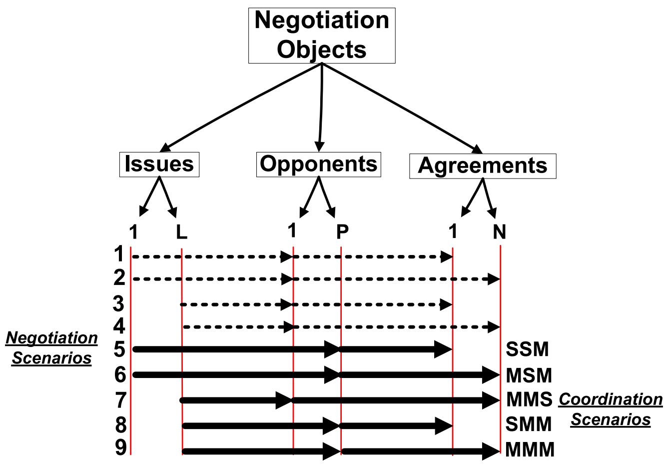


Figure 4.1: *Negotiation scenarios*

Each of the three sub-nodes of the *negotiation objects* node shown in Figure 4.1 has a cardinality of 1 or many. The *Agreements node* in Figure 4.1 refers to agreements over objects given that each negotiation object requires one agreement. Saying that an agent needs to reach N agreements is equivalent to saying that an agent needs to secure N objects. When an agent seeks an agreement over multiple objects, it means that the objects are distinct. For example, a *camera* and a *TV* are two distinct objects. If the aim of a buyer is to negotiate with a seller agent for the purpose of buying two identical objects (e.g., two cameras), then the model used in this work considers the two identical cameras as one object taking into consideration the issues that can be combined such as price and weight. When a buyer agent aims to buy several identical objects, it can use this fact to strengthen its bargaining power. When many buyers decides to make a coalition and submit one proposal to buy several objects at once, that can help in strengthening the bargaining power of the buyer agents. However, the agent coalition problem is not investigated here. For more information about agent coalition, see [52] [76] [128].

As negotiation is one of the important interaction mechanisms in multi-agent systems, considering the main criteria of negotiation objects (i.e., the number of issues per object and the number of providers (opponents) per object) as shown in Figure 4.1, nine negotiation scenarios are recognized. Amongst the nine negotiation scenarios, five are identified and called *coordination scenarios*, namely, scenarios **SSM**, **MSM**, **MMS**, **SMM** and **MMM** where the first letter stands for the number of negotiation objects required, single or multiple, the second letter stands for the number of issues per negotiation object, single or multiple and the third letter stands for the number of provider(s) per object, single or multiple. For example, the **SMM** stands for the coordination scenario where an agent seeks a single object characterized by multiple issues and there are multiple providers for that object. These coordination scenarios are the study target of this thesis. The coordination scenarios are investigated and a dynamic negotiation strategy(s) is/are proposed for each. The proposed negotiation strategies control the bidding process of a buyer agent negotiating concurrently with multiple seller agents for the purpose of procuring one or more objects. All the coordination scenarios end with the letter **M** except the scenario **MMS**. The scenario **MMS** targets the monopolistic markets where each object has a single provider.

As mentioned earlier, we assume that the number of objects is equal to the number of agreements. Accordingly, we can decide whether an agent aims to procure one object or more by looking at the arrow targeting the agreements node. If the arrow ends at 1 in Figure 4.1, then the number of objects is 1, otherwise the number of objects is more than 1. The same logic applies for the issues and opponents nodes.

The first four scenarios shown with the dotted arrows in Figure 4.1 assume agents undertake bilateral (i.e., one-to-one) negotiation where two agents engage in negotiation. Scenario 1 in Figure 4.1 represents a situation where an agent is negotiating with one opponent over one object characterized by a single issue. Negotiation scenario 2 refers to a situation where an agent is negotiating with an opponent agent over multiple objects ($N > 1$) given that each object has a single issue. For example, a buyer agent can negotiate with an electronic store agent over buying a TV and a camera of specific criteria given that the only negotiation issue for each is the price issue. Negotiation scenario 3 refers to a situation where an agent is negotiating with an opponent over a single object characterized by several issues ($L > 1$). For example, an agent may negotiate with a cloud storage provider over renting a storage space. The storage space contains the issues: Price, storage size and duration of the storage.

Finally, scenario 4 describes a situation where an agent is negotiating with an opponent over multiple objects given that each object is characterized by several issues. For example, a buyer agent can negotiate with an electronic store agent over buying a camera and a TV given that each of them is characterized by several issues such as price, warranty, delivery time, etc. This scenario is similar to scenario 7 (coordination scenario **MMS**). The coordination scenario **MMS** assumes that each object has a different provider while scenario 4 assumes that all objects under negotiation have one provider. The coordination approach proposed for scenario **MMS** may also apply for negotiation scenario 4. However, in coordination scenario **MMS**, the variation in the preference profiles of different agents are assumed to be more than the variation in the preference profile assumed in negotiation scenario 4. For example, if all objects have the same provider agent, then its preference over the price issue can be similar across all objects while in case of scenario **MMS**, one provider may care about the price more than about delivery time while other agents may have the opposite preference. Since the proposed coordination mechanisms are based on the assumption of preference variations amongst the opponent agents, the coordination approach used in coordinating the bidding strategy in scenario **MMS** is more effective than in scenario 4.

Since the work of this thesis focuses on coordinating the bidding strategy in one-to-many negotiation, the bilateral negotiation is not investigated per se. However, some of the offer generation methods used in bilateral negotiations are adopted in the one-to-many setting.

The coordination scenario **SSM** represents an agent negotiating with multiple opponents over a single object characterized by a single issue. In real life, one may contact several sellers before deciding to buy from any. For example, an agent can negotiate concurrently with several opponents to buy a specific type of camera. This scenario is investigated in Chapter 5. The difference between coordination scenarios **SSM** and

MSM is that an agent in scenario **MSM** is negotiating with multiple opponents for the purpose of procuring several objects given that each object has multiple providers. Each object in scenarios **SSM** and **MSM** has a single issue. As a real life example for scenario **MSM**, a customer seeks to book both a flight and a room in a hotel by negotiating with several carriers and several hotels. In this case, a customer agent negotiates concurrently with several agents that can provide flight booking and several agents that can provide hotel booking assuming that the customer agent seeks to secure the best deals on the price of each, hence the price would be the only issue of negotiation for both objects. Scenario **MSM** is investigated in Chapter 7.

Coordination scenario **MMS** refers to a situation where the purpose of an agent is to secure multiple distinct objects (and hence multiple agreements are required) given that each distinct object has *one* provider. This situation exists in *monopoly markets* where there is only a single seller offering a certain product. When a buyer agent needs to procure several distinct objects in a monopoly market, there would be a single provider for each object.

The coordination scenario **SMM** represents an agent negotiating with several opponents for the purpose of securing an object characterized by several issues. This situation is abundant in real life. For example, an agent may find several carrier agents to negotiate with over booking a flight. In this scenario, the customer agent cares, for example, about the price, the date and the time of the flight that constitute the issues of negotiation. This scenario is investigated in Chapter 6 where a meta-strategy is proposed to coordinate the bidding strategy during negotiation.

Finally, the coordination scenario **MMM** considers a situation where an agent seeks to secure several agreements over several objects given that each object has several providers and several negotiation issues. This scenario is the most complex one. It exists in markets where there are several providers for each distinct object and each object contains multiple issues. For example, an agent can negotiate with several cloud service provider agents (e.g., Amazon EC2, Google App Engine, AT&T Synaptic, etc.) over a storage space and computations power in the cloud. The storage space can have several issues such as price, size, duration, etc. The computational power can have issues like price, response time etc. This scenario is investigated in Chapter 7.

4.3 Solution Approach

When a buyer agent engages into multi-bilateral concurrent negotiation with a set of seller agents, the buyer agent needs to coordinate its actions (see Section 4.1) against its opponents in each negotiation round to achieve one or more of the negotiation objective criteria such as utility gain and agreement rate.

Formally, let Ω^a be the negotiation strategy of an agent a, then $\Omega^a = \langle IV^a, RV^a, T^a, \Theta^a \rangle$, where $IV^a, RV^a, T^a, \Theta^a$ represent the vector of the initial offer/counteroffer values, the vector of the reservation values, the deadlines vector and finally the vector of the offer/counteroffer generation tactics of an agent a.

Our representation of an agent's a strategy vector (i.e., Ω^a) is similar to its representation in [38]. The difference is that the fourth part of the strategy vector in [38] represents the value β which is a parameter of functions normally used in the time-dependent tactics, while the fourth part in our representation (i.e., Θ^a) is a more general: it indicates any possible offer/counteroffer generation tactic, e.g., trade-off, time-dependent, behavior-dependent etc., its associated parameters (e.g., β value) and constraints. For example, if an offer generation tactic calculates a value beyond the reservation value of an issue, then there should be a constraint to modify that value to be the reservation value of that issue.

A change to any of the Ω^a components during negotiation is considered a change in agent a's negotiation strategy. In this thesis, the negotiation strategy and the bidding strategy are used interchangeably. In our work, we investigate how a bidding strategy for each of the buyer agent delegates (a delegate is a component in the buyer agent that interacts with one opponent agent, see Section 3.2) can be dynamically managed or coordinated taking into consideration the behaviors of the *active opponents* during negotiation. An active opponent is an opponent whose last offer is neither *accept* nor *withdraw*, see Section 3.2. Based on the offers received from an active opponent, two methods can be used to evaluate the opponent, the first one is called the *difference in concession measure* (*DIC*) and the second one is called the *last offer utility* (*LOU*) measure. The *LOU* uses the utility of the received last offers from all agents. When the buyer agent uses *DIC* measure to evaluate the opponent agents, a data preparation procedure is required.

To manage the bidding strategy during negotiation (in real-time) for a buyer agent negotiating concurrently with multiple seller agents assuming that the information about each seller agent is the sequence of the offers received from each during the current negotiation instance, the following steps are implemented:

1. select an appropriate strategy component(s) for manipulation. The selection of a particular component for manipulation depends mainly on the coordination scenario. For example, a trade-off negotiation mechanism is not an option in coordination scenarios **SSM** and **MSM** since there is a single negotiation issue and the negotiation game is of *zero-sum* type. Another factor is the type of the counteroffer generation tactic the buyer agent chooses to use. For example, if the buyer agent chooses to use the time-dependent tactics to generate counteroffers, then the only parameters that can control the process of counteroffer generation are the convexity and deadline parameters. In this case, these two parameters are the only options that can be used to manage the bidding strategy during negotiation.

2. the offers from each opponent is treated as a mathematical sequence and for each sequence, the *first order-difference* (see [12]) sequence is constructed in each negotiation round. Let $X^t_{\mathbb{s}_i \to \mathbb{d}_i}[j_l] =< x^{t-1}_{\mathbb{s}_i \to \mathbb{d}_i}, x^{t-2}_{\mathbb{s}_i \to \mathbb{d}_i}, ..., x^{t=0}_{\mathbb{s}_i \to \mathbb{d}_i} >$ be the sequence of offers sent from a seller agent $\mathbb{s}_i$ to a buyer's delegate $\mathbb{d}_i$ over the issue j_l and let t be the current time, $\Delta\mathbb{s}_i =< |x^{t-1}_{\mathbb{s}_i \to \mathbb{d}_i} - x^{t-2}_{\mathbb{s}_i \to \mathbb{d}_i}|, |x^{t-2}_{\mathbb{s}_i \to \mathbb{d}_i} - x^{t-3}_{\mathbb{s}_i \to \mathbb{d}_i}|, ..., |x^{1}_{\mathbb{s}_i \to \mathbb{d}_i} - x^{t=0}_{\mathbb{s}_i \to \mathbb{d}_i}| >$, where $\Delta\mathbb{s}_i$ is the first order difference of the sequence $X^t_{\mathbb{s}_i \to \mathbb{d}_i}[j_l]$. The absolute sign is used to accommodate for two situations: the first case is when the initial offer value of a negotiation issue is larger than the reservation value of that issue, such as the price issue for a seller agent. The second case is when the initial value of an issue is smaller than the issue's reservation value, such as the quantity issue for a seller agent. The $\Delta\mathbb{s}_i$ is calculated for each seller in each negotiation round. Analogously, the $\Delta\mathbb{d}_i$ is found for each delegate $\mathbb{d}_i$ where the sequence is used to calculate $\Delta\mathbb{d}_i$ is $X^t_{\mathbb{d}_i \to \mathbb{s}_i}[j_l]$. Depending on the mental state of the buyer agent, the concession behavior during any part (partial sum or total sum) of the history of the offers received from a seller agent $\mathbb{s}_{\mathbb{i}}$ during the current negotiation instance can be used to evaluate the behavior of the seller agent $\mathbb{s}_{\mathbb{i}}$. The sum of each $\Delta\mathbb{s}_i$ is used if the buyer agent considers the total concession of a seller agent since the start of negotiation. If the buyer considers only the recent concession, it might consider the first element

in $\Delta\mathbb{s}_i$, etc. If the buyer agent assume that the behaviors of the seller agents are dynamic and non consistence, then it might consider the recent concession only.

3. during negotiation, the behavior of each seller agent is compared to the behavior of its delegate counterpart. In other words, we do pairwise comparison between the concession of a buyer's delegate and its counterpart seller agent. The reason is that different buyer's delegates may behave differently during negotiation. For example, if the vector of the first elements in each $\Delta\mathbb{s}_{\mathbb{i}}$ is <$3,$7,$2,$10,$4> and the vector of the first elements in each $\Delta\mathbb{d}_{\mathbb{i}}$ is <$2,$5,$4,$12,$3>, then the pairwise comparison involve finding the difference between the two vectors, <$3,$7,$2,$10,$4> - <$2,$5,$4,$12,$3> = <$1,$2,$-2,$-2,$1>. It is obvious that if we take the absolute amount of concession of each seller without doing the pairwise comparison, the seller agent number 4 is offering the largest concession ($10). By doing the pairwise comparison we decide that the seller agent number 4 is as good as the seller agent number 3, while the best seller agent from the buyer agent point of view is the seller agent number 2.

4. the information obtained in points 2 and 3 are used to manipulate the component(s) of point 1

5. counteroffers are generated according to the updated bidding strategy.

6. at the start of a new negotiation round, **goto** 1

Steps 2 and 3 above are the *data preparation* procedure necessary for the **DIC** measure. The described steps are a general solution approach that can be used to manage the bidding strategy of a buyer agent negotiating with multiple seller agents concurrently. Similarly, the same approach can be adopted by a seller agent negotiating with multiple buyer agents concurrently. The realization of the above steps are shown in the next chapters.

The above approach is based on the following assumptions:

- agents are self-interested aiming at maximizing their utility gain per agreement and willing to cooperate - if possible - to reach a win-win agreement

- agents keep their preferences and strategies private

- agents negotiate in a dynamic and open environment and their behavior can be different in each new negotiation instance.
- the problem of reputation is not considered here for the same reason stated in the previous point. In an electronic market, we assume that customers and sellers can create agents with different identities each time. In addition, the dynamic and ever changing market causes inconsistent patterns of behavior by both, buyers and sellers.

The buyer agent needs to process or prepare the offers/counteroffers related data at the start of each negotiation round, Example 4.1 shows an example about data preparation. Data preparation is important for the proposed dynamic negotiation strategies.

Table 4.1: *Example of three negotiation rounds*

Rounds	Sellers	Offers/Counteroffers						Buyer	Rounds
		j_1	j_2	j_3	j_3	j_2	j_1		
0	s_1	100	60	24	7	10	20	d_1	0
0	s_2	150	65	30	7	10	20	d_2	0
0	s_3	140	80	35	7	10	20	d_3	0
1	s_1	90	55	20	11	15	25	d_1	1
1	s_2	120	58	26	11	15	25	d_2	1
1	s_3	115	70	27	11	15	25	d_3	1
2	s_1	74	48	16	14	21	33	d_1	2
2	s_2	95	49	17	14	21	33	d_2	2
2	s_3	100	50	19	14	21	33	d_3	2

Example 4.1 Data preparation illustration

In this example, we assume a buyer agent is negotiating with three seller agents of the same object characterized by the set of issues $J = \{j_1, j_2, j_3\}$. Table 4.1 shows the values of the offer values proposed by the seller agents and the counteroffer values proposed by the buyer agent's delegates assuming that the first round starts at time $t = 0$. Table 4.1 shows that the agents exchange 3 offers and 3 counteroffers at every point of time. The monotonicity concession behavior for agents are assumed. Consider the current time $t = 3$:

1. $X^3_{\mathbb{d}_1\to\mathbb{s}_1}[J] \;=< x^2_{\mathbb{d}_1\to\mathbb{s}_1}[J], x^1_{\mathbb{d}_1\to\mathbb{s}_1}[J], x^0_{\mathbb{d}_1\to\mathbb{s}_1}[J] > = << 33, 21, 14 >, < 25, 15, 11 >, < 20, 10, 7 >>$.

2. $\Delta\mathbb{d}_1 \;= << |33-25| = 8, |25-20| = 5 >, < |21-15| = 6, |15-10| = 5 >, < |14-11| = 3, |11-7| = 4 >>$

3. $X^3_{\mathbb{d}_2\to\mathbb{s}_2}[J] \;=< x^2_{\mathbb{d}_2\to\mathbb{s}_2}[J], x^1_{\mathbb{d}_2\to\mathbb{s}_2}[J], x^0_{\mathbb{d}_2\to\mathbb{s}_2}[J] > = << 33, 21, 14 >, < 25, 15, 11 >, < 20, 10, 7 >>$.

4. $\Delta\mathbb{d}_2 \;= << 8, 5 >, < 6, 5 >, < 3, 4 >>$.

5. $X^3_{\mathbb{d}_3\to\mathbb{s}_3}[J] \;=< x^2_{\mathbb{d}_3\to\mathbb{s}_3}[J], x^1_{\mathbb{d}_3\to\mathbb{s}_3}[J], x^0_{\mathbb{d}_3\to\mathbb{s}_3}[J] > = << 33, 21, 14 >, < 25, 15, 11 >, < 20, 10, 7 >>$.

6. $\Delta\mathbb{d}_3 \;= << 8, 5 >, < 6, 5 >, < 3, 4 >>$.

7. $X^3_{\mathbb{s}_1\to\mathbb{d}_1}[J] \;=< x^2_{\mathbb{s}_1\to\mathbb{d}_1}[J], x^1_{\mathbb{s}_1\to\mathbb{d}_1}[J], x^0_{\mathbb{s}_1\to\mathbb{d}_1}[J] > = << 74, 48, 16 >, < 90, 55, 20 >, < 100, 60, 24 >>$.

8. $\Delta\mathbb{s}_1 \;= << |74-90| = 16, |90-100| = 10 >, < |48-55| = 7, |55-60| = 5 >, < |16-20| = 4, |20-24| = 4 >>$.

9. $X^3_{s_2\to d_2}[J] \;=< x^2_{s_2\to d_2}[J], x^1_{s_2\to d_2}[J], x^0_{s_2\to d_2}[J] >=<< 95, 49, 17 >, < 120, 58, 26 >, < 150, 65, 30 >>$.

10. $\Delta\mathbb{s}_2 \;= << 25, 30 >, < 9, 7 >, < 9, 4 >>$.

11. $X^3_{s_3\to d_3}[J] \;=< x^2_{s_3\to d_3}[J], x^1_{s_3\to d_3}[J], x^0_{s_3\to d_3}[J] > = << 100, 50, 19 >, < 115, 70, 27 >, < 140, 80, 35 >>$.

12. $\Delta\mathbb{s}_3 \;= << 15, 25 >, < 20, 10 >, < 8, 8 >>$.

13. $\Delta F_1 \;=\; \Delta s_1 - \Delta d_1 \;= << 16, 10 >, < 7, 5 >, < 4, 4 >> - << 8, 5 >, < 6, 5 >, < 3, 4 >> \;= << 16-8 = 8, 10-5 = 5 >, < 7-6 = 1, 5-5 = 0 >, < 4-3 = 1, 4-4 = 0 >>$, where the $\Delta^1 F$ refers to the difference between the first order-differences of the seller s_1 and the delegate d_1.

14. $\Delta F_2 = \;\Delta s_2 - \Delta d_2 \;= << 25, 30 >, < 9, 7 >, < 9, 4 >> - << 8, 5 >, < 6, 5 >, < 3, 4 >> \;= << 17, 25 >, < 3, 2 >, < 6, 0 >>$, where the $\Delta^2 F$ refers to the difference between the first order-differences of the seller s_2 and the delegate d_2.

15. $\Delta F_3 = \;\Delta s_3 - \Delta d_3 \;= << 15, 25 >, < 20, 10 >, < 8, 8 >> - << 8, 5 >, < 6, 5 >, < 3, 4 >> = << 7, 20 >, < 14, 5 >, < 5, 4 >>$, where the $\Delta^3 F$ refers to the difference between the first order-differences of the seller s_3 and the delegate d_3.

16. $F^{(0,t-1)}_{j_1} \;= < 8+5 = 13, 17+25 = 42, 7+20 = 27 >, \;\; F^{(1,t-1)}_{j_1} =< 8, 17, 7 >$.

17. $F_{j_2}^{(0,t-1)} =< 1+0=1, 3+2=5, 14+5=19 >,$ $F_{j_2}^{(1,t-1)} =< 1, 3, 14 >.$

18. $F_{j_3}^{(0,t-1)} =< 1+0=1, 6+0=6, 5+4=9 >,$ $F_{j_3}^{(1,t-1)} =< 1, 6, 5 >.$

19. $F^{t-1,t} =< F_{j_1}^{(t-1,t)}, F_{j_2}^{(t-1,t)}, ... >$

The result of the pairwise comparison between the seller agents of issue j_l and their counterparts delegates are denoted by $F_{j_l}^{(t_1,t_2)}$. The t_1 and t_2 are *the conceding time interval* (**CTI**). The **CTI** includes the start time and the end time in the current negotiation thread where the concessions of agents are considered. For example, at time $t = 3$, the $F_{j_1}^{(0,t-1)}$ indicates that the buyer agent considers all the concessions from the starting time of negotiation till time $t = 2$ whereas the $F_{j_1}^{(1,t-1)}$ indicates that it considers the concessions from time $t = 1$ till time $t = 2$. The buyer agent decides the values of t_1 and t_2 depending on its belief about the important time interval of opponents' behaviors. If it believes that the recent concessions are the most important ones, then the first elements (or the first few elements) in the ΔF are considered.

By inspecting our example, the $F_{j_3}^{(0,t-1)} = < 1, 6, 9 >$ is the pairwise comparison of the seller agents' concessions on the first issue (j_1). It shows that the agent number 3 is the most generous while agent number 1 is the least generous. When we consider only the recent concessions, $F_{j_3}^{(0,t-1)} = < 1, 6, 5 >$, the agent number 2 is the most generous agent. This example shows that choosing the location and the length of the time interval ($[t_1, t_2]$) of the current negotiation instance can affect the process of coordination in terms of distinguishing between the behaviors of different agents. In our experiments, two situations are considered, the recent concessions and the total concessions up to the current negotiation round.

Example 4.1 shows an illustration for data preparation when a buyer agent is negotiating with three same object sellers where the purpose is to secure one object. Similar approach is used to process the current negotiation threads (see Section 3.2) for more complex scenarios. Once the $F_{j_l}^{(t_1,t_2)}$ is found for each issue, the proposed coordination mechanisms utilizes the current information in controlling one or more of the strategy components during negotiation. The difference in concession method is one possible approach to evaluate the behavior of a seller agent. A second approach to evaluate the behaviors of the seller agents is to compare the utility values of their last proposed offers. More detail about the second approach is presented in Chapter 5.

Since seller agents are assumed to be competitive and self-interested during negotiating, the buyer agent plays tough with the conceding seller agents and behaves more lenient with the tough negotiating agents. The reason is that, a conceding agent is more desperate to reach an agreement than a tough negotiating agent. The buyer agent seeks to reach a high utility agreement with a conceding agent and reach an agreement with tough agents since the worst case for the buyer agent is not to reach an agreement. However, the proposed negotiation strategies consider the welfare of other agents when agents are negotiating over objects characterized by several issues given that agents have divergent preferences over issues. The proposed *iterative offer generation* mechanism is designed to be competitive and cooperative. It is competitive in case the proposing agent using a concession strategy and cooperative when the proposing agent uses a trade-off strategy, see Chapter 6 for details.

4.4 Global and Local Reservation Values

As reservation values are part of an agent negotiation strategy and since Chapter 7 focuses on managing the *local* reservation values during negotiation, it is important to differentiate between *global* and *local* reservation values. We assume that global reservation values are fixed during negotiation while local reservation values are subject to change during negotiation. For example, a buyer agent negotiates over 2 objects o_1 and o_2 which are characterized by the price issue. The buyer's budget, which is \$100, is the global reservation value. The global reservation value can be divided amongst the two objects' common issue, i.e., the price issue. Assume that the buyer agent valuates the object o_1 by \$60 and the object o_2 by \$40. The values \$60 and \$40 can change during negotiation but their sum will always be \$100. Hence the \$60 and \$40 are the local reservation values and the \$100 is the global reservation value for the price issue. The same idea is applied for other common issues.

The global and local reservation values are important concepts in negotiation. Almost every one of us practices managing the local reservation values. For example, let us say I need to buy a laptop and a phone and my budget is \$1000. Before checking the market, it would be difficult for me to say how much I would spend on each. I probably could say that the laptop may cost around \$600. It can happen that during the shopping process, I find a sale on a certain laptop brand that brought their prices from

\$1200 down to \$750. In that case, I may allocate the \$750 to buy the laptop and find a phone with around \$250. By doing that, I am managing the local reservation values over my items according to the current information in the market.

In automated negotiation, if a certain resource can be divided amongst different objects such as the price resource, then there would be local reservation values which can be modified during negotiation to achieve the main goal of negotiation which is, for example, buying a certain number of distinct objects given the global reservation value.

4.5 General Experimental Settings

The dynamic negotiation strategies (bidding strategies) proposed in this thesis are evaluated empirically since it is difficult to evaluate the proposed mechanisms theoretically due to the dynamicity nature of the one-to-many negotiation process. In particular, the proposed mechanisms are based on heuristics. Moreover, there are a number of interrelated negotiation variables that can affect the outcome of the negotiation process such as different negotiation tactics, their associated parameters and deadlines which makes theoretical validation difficult. The proposed algorithms are tested against sets of negotiation variables that are constructed from using different combinations of these variables to represent a realistic situation. For each different combination of variables, experiments are conducted and results are analyzed.

The objectives of the proposed coordinated negotiation models to be maximized are both, the utility of an agreement and the total number of agreements. In addition, some models are tested for possible social welfare gain. In short, the dependent variables in the proposed models are utility rate, agreement rate and social welfare. On the other hand, there are many independent variables such as deadlines, overlaps, tactics and their parameters, etc. More detail about the specific independent variables considered in the experiments are discussed in the chapters to come. The next two sections discuss the simulation environment and the general experimental setup.

4.5.1 Simulation Environment

The Mathematica 8.0 in the Wolfram Workbench 2[1] environment is the technology and platform used for building and running the experiments. Figure 4.2 shows a snapshot of the development environment. The proposed negotiation strategies are structured according to the specific coordinated negotiation scenario. Accordingly, the experimental works are grouped in different projects. Some functions are used across different projects such as the time-dependent and behavior-dependent offer generation mechanisms.

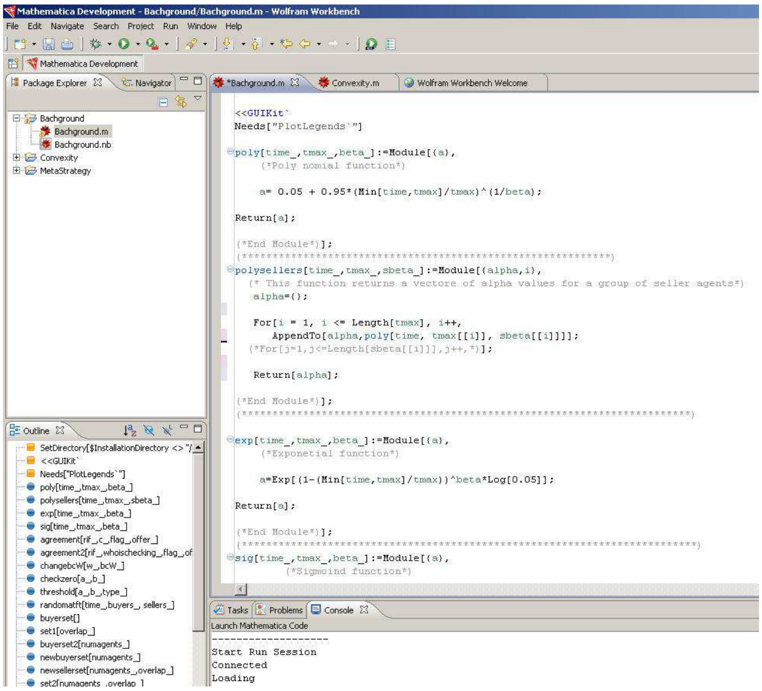


Figure 4.2: *A snapshot of the experimental working environment*

An agent in the experiments is abstracted as a negotiation strategy that generates offers and counteroffers. In addition, it determines when to accept an offer and when to withdraw from negotiation.

[1]Wolfram Workbench: www.wolfram.com/products/workbench/

4.5.2 Experimental Settings

Heuristic-based offer generation methods are often used in the negotiation literature to evaluate different negotiation strategies, e.g., [33][38] [4]. The heuristic methods discussed in sections 2.3.3.1 and 2.3.3.3 are used to generate offers and counteroffers by different agents. As shown in Section 2.3.3.1, time-dependent tactics contain three -broadly speaking- types of concession behaviors: Boulware, linear and conceder. If we use a combination of them to generate an offer using weights indicating the percentage of participation of each type in the offer, wide range of offer types can be created. When the behavior-dependent tactics are mixed with the time dependent-tactics, a wider range of offers can be generated that reflect different possible types of agents. Accordingly, the mixing technique ensures that the results of the experiments are more robust. As explained in Section 2.3.3.3, the behavior-dependent tactics are reactive towards the opponent concessions since they imitate the concession of the opponent. Mixing a resource dependent offer generation method such as time-dependent with a reactive offer generation method such as behavior-dependent assures testing the proposed dynamic negotiation strategies against large and different possible types of opponents. Table 4.2 shows a sample of tactics and the their intervals of weights.

Polynomial decision function: (Time-dependent)	Conceder: PC $= \{\beta \| \beta \in [2, 10]\}$ Linear: PL $= \{\beta \| \beta \in [0.9, 1]\}$ Boulware: PB $= \{\beta \| \beta \in \ [0.1, 0.8]\}$
Mixing of time-dependent tactics:	MTD: $PC * r_1 + PL * r_2 + PB * r_3, \sum_{i=1}^{3} r_i = 1$
Behavior-dependent	concession Tit-For-Tat: $a \in [0, 0.5)$ $A = 1 - a$
Weights	Small: S $= \{\mu \| \mu \in [0.1, 0.3]\}$ Medium: M $= \{\mu \| \mu \in (0.3, 0.6]\}$ Large: L $= \{\mu \| \mu \in (0.6, 0.9]\}$

Table 4.2: *Negotiation tactics, their parameters and weights for possible mixing between different tactics*

In Figure 2.4, the polynomial and the exponential concession functions show somehow different convexity at different β values. For example, the linear behavior of the exponential function lies roughly between 2 and 4, i.e., $\beta \in [2, 4]$ whereas the linear behavior for the polynomial function happens when $\beta = 1$. Values of β that are near

1 also show close to linear behavior for the polynomial function. The values in Table 4.2 reflect the behavior of the two functions. Since the Sigmoid function behaves differently from the polynomial and the exponential, it is excluded from the experiments. For the behavior-dependent tactic, the *concession Tit-For-Tat* tactic is chosen because its flexibility, see Section 2.3.3.4.

The negotiation tactics shown in Table 4.2 and their parameters can be mixed to produce a range of different concession behaviors. The Cartesian product between the different components in Table 4.2 can be applied to generate a set of hybrid tactics. For example, a set containing the polynomial time-dependent tactics and the behavior-dependent tactics using different weights to mix between them is shown in Equation 4.2.

$$\begin{aligned} ST &= \{polynomial\} \times \{concession\, Tit - For - Tat\} \times \{weights\} \\ ST &= \{PC, PL, PB\} \times \{a, A\} \times \{S, M, L\} \end{aligned} \tag{4.2}$$

The following is the result of applying the Cartesian product in Equation 4.2:

$$\begin{aligned} ST = \{&(PC \times a \times S), (PC \times a \times M), (PC \times a \times L), (PC \times A \times S), \\ &(PC \times A \times M), (PC \times A \times L), (PL \times a \times S), (PL \times a \times M), \\ &(PL \times a \times L), (PL \times A \times S), (PL \times A \times M), (PL \times A \times L), \\ &(PB \times a \times S), (PB \times a \times M), (PB \times a \times L), (PB \times a \times S), \\ &(PB \times A \times M), (PB \times A \times L)\} \end{aligned} \tag{4.3}$$

Since the polynomial and the exponential functions behave similarly, the polynomial function is used to generate offers and counteroffers by agents when they use the time-dependent tactics. In the context of mixed tactics used in this thesis, an abbreviation such as *PCaS* means the mixed tactic *PCaS* uses the polynomial function with a conceder behavior mixed with the *concession Tit-For-Tat behavior-dependent* (see Equation 2.11) tactic where the contribution of the *concession Tit-For-Tat behavior-dependent* in the final offer is small, i.e., $S = \{\mu | \mu \in [0.1, 0.3]\}$. Finally, the a in *PCaS* means that the contribution of the opponent's previous concession is a small part ($a \in [0, 0.3]$, see Table 4.2) of the offer being proposed using the *concession Tit-For-Tat behavior-dependent* tactic, see Equation 2.11, whereas A indicates the opposite, see Table 4.2. The rest of the abbreviations can be interpreted analogously. In some experiments, the random absolute Tit-For-Tat is used instead, see Equation 2.9.

Each member of the ST set (see Equation 4.3) represents a subset of related concession behaviors (the β parameter within the conceder behavior can have different values, see Table 4.2) to ensure that the proposed bidding strategies are tested against a wide range of opponents' behaviors. In other words, to improve the diversity of opponent's behaviors, there are distinct groups of behaviors and the members of each distinct group shows some variation. Specific experimental settings are presented in the experimental evaluation part of each chapter.

The Mixing of time-dependent tactics (*MTD*) is introduced to ensure more variety in the behavior of the opponent agents. The set $r^{'} = \{r^{'}_1, r^{'}_2, r^{'}_3\}$ is generated randomly from the interval $[0, 1]$, then it is divided by its total ($r = r^{'}/sum(r^{'})$) to make sure that the total of $r = \{r_1, r_2, r_3\}$ equals 1. The previously generated *PC,PL,PB* are multiplied by the set r as shown in Table 4.2.

In the experimental part of this thesis, we consider that agents are mostly driven by their internal resource(s) such as time. However, in some experiments, the seller agents are designed to use tactics that mix between the behavior-dependent and the time-dependent tactics given that the contribution of the behavior dependent-tactics in the final offer values are small to medium. The reason is that the actions of agents are subject to the availability of certain resources and if agents are imitating their opponents and do not care about the availability of their resources, e.g., time, then they will just imitate their opponents which seems irrational and naive. If two agents do not have time limitation, then the dominant strategy for an agent is to offer the minimum amount of concession imposed by the system. If the opponent agent imitates its counterpart, it will propose similar amounts of concessions. Given the situation, it can not be sure that the two agents can reach an agreement within a reasonable time frame especially if the minimum amount of allowed concession is very small.

In addition to the behaviors of the opponents in terms of their negotiation strategies, two other important negotiation environmental factors need to be taken into consideration: *The percentage of overlap and the deadlines*. The percentage of overlap determines the length of the *agreement zone* between negotiators. The overlap percentage between the reservation value intervals of negotiation issues is an important factor for the result of the final outcome of the negotiation process. In case the percentage of the overlap is zero, then reaching an agreement becomes impossible. For example, assume that the reservation interval for the price issue of a buyer agent is $[10, 20]$ and the reservation interval for the price issue of an opponent seller agent is $[40, 21]$. In this case the buyer agent, ultimately, will offer its reservation price as the last option which is 20 and the seller agent offers its reservation price as the last proposal which is 21. It is obvious that the two agents will not come to an agreement because the overlap between their reservation intervals is zero. In other words, there is no agreement zone between the two agents.

The ramification of having small overlap percentage(s) (i.e., small agreement zones) and agents having different deadlines is that the chance for reaching an agreement becomes slight since a buyer agent may concede up to its reservation price at its deadline. At the same time, the seller agents can have different deadlines which means it can be difficult to guarantee that at least one seller agent has the same deadline as the buyer agent. If a seller agent and the buyer agent has the same deadline, then both will offer their reservation value at the same time an agreement is reached.

In some experiments, different percentages of overlaps are incorporated to test for the effect of the length of the agreement zone length on the negotiation outcome. Suppose that an agent $\mathbb{d}$ has the reservation interval $[min^{\mathbb{d}}_{j_l}, max^{\mathbb{d}}_{j_l}]$ for an issue j_l, the reservation interval of the issue j_l of an opponent agent $\mathbb{s}$ is calculated as follows:

$$[min^{\mathbb{s}}_{j_l}, max^{\mathbb{s}}_{j_l}] = \begin{cases} min^{\mathbb{s}}_{j_l} = min^{\mathbb{d}}_{j_l} + \Phi_{j_l}(max^{\mathbb{d}}_{j_l} - min^{\mathbb{d}}_{j_l}) \\ max^{\mathbb{s}}_{j_l} = min^{\mathbb{s}}_{j_l} + (max^{\mathbb{d}}_{j_l} - min^{\mathbb{d}}_{j_l}) \end{cases} \tag{4.4}$$

In Equation 4.4, Φ_{j_l} is the overlap percentage ($\Phi_{j_l} \in [0, 1]$) that determines the agreement zone length between the two agents for the issue j_l. For example, when $\Phi_{j_l} = 0$, there is a complete overlap while if $\Phi_{j_l} = 1$ then the two agents meet exactly at their reservation values and an agreement is only possible if both agents offer their reservation values. If $\Phi_{j_l} = 0.4$, then the percentage of the overlap is 60% etc. Using different Φ_{j_l} values result in different percentages of overlaps.

The deadline is an important factor in negotiation. In real negotiation environment, the length of the negotiation time is finite and can be determined either by the negotiation environment or by the individual agents. If the deadline is determined by the environment then all agents will have the same deadline, otherwise, each agent chooses its own deadline according to its mental state. Deadlines are related to reservation values in the sense that agents offer their reservation values at their deadlines. In addition, a deadline is a parameter used in the time-dependent tactics to decide the value of an offer for the next negotiation round.

The number of exchanged messages in terms of offers and counteroffers between agents coined in the term *negotiation rounds* can be used instead of considering the real negotiation time for testing different negotiation strategies which is a widely used approach in the negotiation literature, e.g., [35][164][40]. In this thesis, the concept of negotiation round is used and one negotiation round is equivalent to one time unit. A negotiation round involves the exchange of two offers between two agents. If an agent $\mathbb{s}$ starts a negotiation round by proposing an offer at time $t = 0$, then an opponent agent $\mathbb{d}$ replies with a counteroffer at $time = 1$. This makes a complete negotiation round. For example, if the deadline is assumed to be 20 then the number of negotiation rounds is 20 and each agent proposes 20 offers and receives 20 counteroffers etc.

The results of the experiments are averaged and plotted. The error-bars are shown to indicate the significance of the results. In addition, the Mann-Whitney test [85] is used to ensure that the differences between the results are statistically significant at 95% confidence level.

4.6 Summary

This chapter introduces the coordination problem in the one-to-many negotiation. An agent (a buyer agent in our case) is assumed to conduct multi-bilateral negotiations with a group of seller agents concurrently given that the buyer's concurrent negotiations have a common goal. Accordingly, the state of a certain instance of negotiation can affect the state(s) of the other instances. In other words, the concurrent negotiations can be interdependent. The interdependency between different negotiations causes the need for coordination.

Section 4.2 in this chapter classifies possible negotiation scenarios and names the 5 one-to-many negotiations as coordination scenarios. The reason for choosing this name is that the negotiation scenarios require coordination between the concurrent negotiations of each type given the assumption that they aim to achieve a common goal. The classification scheme is based on the numbers of the main components of any negotiation: objects, issues and providers. The number of these components can be either single or multiple. Since this thesis targets the one-to-many negotiation, the number of the opponents per object is assumed to be multiple, except for the case when the objective of the buyer agent is to procure multiple distinct objects in a monopolistic market where each object has a single provider.

The solution approach for coordinating multiple negotiations is presented in Section 4.3. The proposed approach assumes that the only available information during negotiation is about the offers received from the current seller agents. Since the buyer agent is assumed to receive, most of the times, multiple offers at every negotiation round, the received offers are compared against each other and against the concessions offered by their delegate partners in terms of the concessions offered. The first-difference order of the received and the proposed offers from a given seller agent and its delegate partner, respectively, are used as input data for the coordination mechanisms. According to the results of the data analyses, the proposed coordination mechanisms decide the next course of action in each negotiation round. The section illustrates the process of data preparation by a numerical example.

Since managing the local reservation values is used by some of the coordination mechanisms in this thesis, the concept of a local reservation value is explained. In addition, the difference between a global reservation value and a local reservation value is discussed and a numerical example is used to provide more clarification. The last part of this chapter presents the general experimental settings that are considered in this thesis. It shows a snapshot of the experimental environment that is used to run the experiments. In addition, it discusses the offer generation tactics that are used to generate offers by different agents in the experiments. Moreover it discusses the different negotiation environmental variables, including the deadlines and the overlap percentages between the reservation intervals of the negotiation issues.

Most of the negotiation mechanisms presented in the one-to-many related work rely on the historical data and/or knowledge about the probability distribution of some key data, e.g., reservation values of the opponents. However, the work presented in this thesis relies on the values of the offers received from the current opponents to decide the next counteroffer value for each opponent agent.

Chapter 5

A Single Negotiation Issue for One or Multiple Objects

This chapter investigates the problem of coordinating the bidding strategy in concurrent one-to-many negotiation in two coordination scenarios: the single object single issue and multiple providers (SSM) coordination scenario and the multiple objects single issue and multiple providers (MSM) coordination scenario. Both scenarios assume one negotiation issue per object. The SSM scenario assumes one object during negotiation whereas the MSM scenario considers multiple distinct objects. Manipulating the convexity of a concession curve is one of the mechanisms that are used in the automated negotiation literature to coordinate multiple concurrent negotiations. A novel mechanism that manipulates the convexity (slop) of different concession curves is proposed to coordinate the bidding strategy for a buyer agent in the SSM scenario. In addition, a different mechanism for manipulating the concession curve convexities for the MSM local coordination scenario is devised. Moreover managing the local reservation values is proposed for coordinating the MSM global coordination scenario. Finally, all the proposed coordination mechanisms are validated empirically.

5.1 Introduction

One of the motivating scenarios that are presented in Chapter 1 is the scientific workflow in the cloud, see section 1.2.1. Such scientific workflows produce large amount of intermediate datasets and require intensive computational power. The generated intermediate datasets are needed either for generating other intermediate datasets or for analysis. When dealing with such scientific workflows, the problem of deleting or storing the intermediate datasets comes in place. When running such scientific workflows on the cloud, the problem of limited storage and computational resources can be avoided since the cloud provides, theoretically, unlimited resources. To improve the utilization of resources on the cloud in terms of both the cost and efficiency of producing a needed dataset from another predecessor dataset(s) during the execution of a certain workflow, we propose provisioning computational power and/or storage space during the execution of the workflow using automated negotiation in real-time. A workflow may need one object like a storage space that can contain the price as the only issue. In the this case, the agent who works on the behalf of the workflow conducts multiple concurrent negotiations with multiple storage space providers on the cloud. This case represents the **SSM** coordination scenario. On the other hand, if the worklow requires more than one object, such as storage space, software application etc., the agent conducts multiple negotiations with multiple cloud providers with the assumption that all the objects contains the same single issue such as price. The second case can be represented by the coordination scenario **MSM**.

The coordination negotiation scenario where a buyer agent is negotiating with multiple seller agents seeking an agreement over a single object of a single issue (**SSM**, see Section 4.2), is targeted by several studies in the negotiation literature, (e.g., [23][161][3][2] [90]). For more information, see Chapter 2.

Section 5.2 presents the proposed coordination mechanism for the **SSM** coordination scenario including the detailed technique and the experimental evaluation. The proposed coordination mechanisms for the **MSM** coordination scenario and the experimental evaluation is presented in Section 5.3. The section includes three mechanisms. The first one is based on managing the local reservation values as a global coordination mechanism, the second one is based on managing the convexity of the concession curves as a local coordination mechanism whereas the third one combines the two mechanisms into a hybrid mechanism.

5.2 SSM Coordination Scenario

The coordination model proposed in this section targets the **SSM** coordination scenario, see Figure 4.1. The objective of the buyer agent in this scenario is to procure one object characterized by a single issue while negotiating with multiple providers. Figure 5.1 shows that the number of the required objects is 1 and the number of the negotiation issues is also one. In addition, the number of buyer's delegates equals the number of the seller agents at any point of time during negotiation. The buyer agent creates a new delegate for each new seller agent and if any seller leaves negotiation, its counterpart delegate is destroyed. Since there is a single negotiation issue, the type of negotiation game is a *zero-sum* game which indicates that each agent seeks to maximize its utility gain without considering the utility gain of its counterpart.

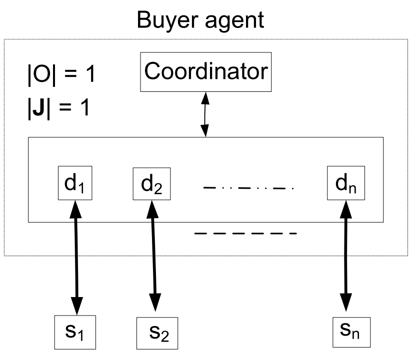


Figure 5.1: *One-to-many negotiation over a single object of a single issue*

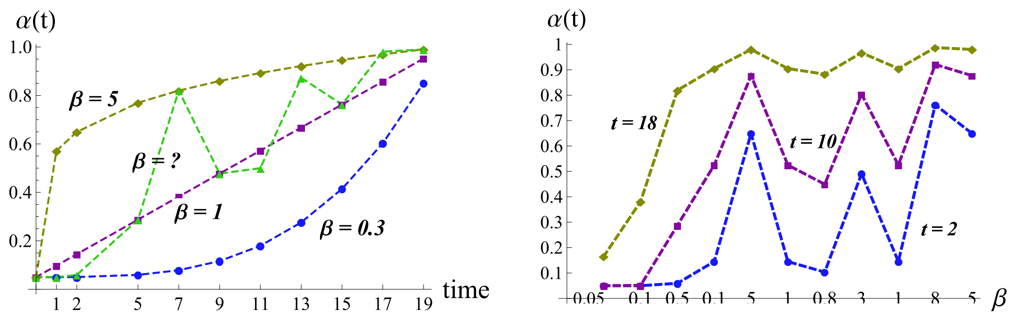
The polynomial and the exponential concession functions are widely used in the literature as mechanisms to determine the concession in every negotiation round in the process of generating offers by agents, see Section 2.3.3.1. The value of the concession function at a certain time during negotiation depends on two parameters, the convexity parameter that is called β and the time elapsed since the start of negotiation which is represented as the number of negotiation rounds in our negotiation model. The proposed negotiation model for the **SSM** coordination scenario depends on managing the convexity of the concession curve during negotiation. The model is presented in the next section.

5.2.1 Managing the Convexity Parameter

As discussed in Section 2.3.3.1 and shown in Figure 2.4, different β values result in different concession behaviors. For the rest of this chapter, unless stated to the contrary, the negotiation strategy means the buyer agent's negotiation strategy.

A coordination mechanism can be presented as a process that requires inputs (independent variables) and produces outputs, i.e., dependent variables. The quality of an output is used to assess the coordination mechanism. The independent variables of the coordination process are the negotiation strategy (Ω) components and the feedback from the opponents, see Section 4.3. Since the reservation value in our scenario is classified as a *global reservation* value, see Section 4.4, it is not possible to update the reservation value during negotiation. Regarding the initial value, it can be determined before the start of negotiation based on some domain knowledge. Two strategy components can be managed in the **SSM** coordination scenario: $\beta \in \Theta$ and the deadline $t_{max} \in T$. The dynamic deadlines approach is left as future work. The other input to the coordination process is the opponent's responses in terms of their proposed offers which are important feedback during negotiation. Other information such as the possible arrivals of new outside options during negotiation can affect the coordination method. However, in our model, we only consider the feedback in terms of the opponents' offers since in many cases, other information may not be available or difficult to estimate. The outputs of the coordination process determine the effectiveness and robustness of the process in fulfilling its goals. Various metrics (dependent variables) can be used to measure the effectiveness and robustness of the coordination process, such as utility, agreement rate and social welfare.

Figure 5.2 shows the effect of different curve convexities on the amount of concession proposed by an agent over an issue j with $IV_j < RV_j$. Figure 5.2a shows 4 different concession curves. Three of them represent the Boulware ($\beta = 0.3$), linear ($\beta = 1$) and conceder ($\beta = 5$) concession curves. The behavior of the three concession curves is smooth and predictable. The fourth concession curve ($\beta =?$) is produced using random β values. The β values used for the curve labeled $\beta =?$ are the ones shown on the *x-axis* of Figure 5.2b. It is obvious that with each different convexity, i.e., different β value, the amount of the offered concession is different. Figure 5.2b shows three concession curves generated with the set of β values shown on the *x-axis* at three different times



(a) β values, different times

(b) β values, time is fixed

Figure 5.2: *The effect of different β values on the concession curve*

where the deadline is assumed to be 20. The figure shows that at smaller times, the amount of concession is always lower at all β values. However, at the same point of time, different β values produce different amounts of concessions.

The idea behind the proposed coordination model (β**C**) is to change the value of β during negotiation according to the collective behaviors of the *in-negotiation* opponents in terms of their concessions. As mentioned is Section 4.3 and according to the assumptions of this thesis, there are two approaches (metrics) that can be used to evaluate the behavior of an agent, the *DIC* and the *LOU* metrics. The *DIC* approach depends on the difference in consecutive concessions of the opponents, whereas the *LOU* depends on the utility value of the last offers.

When using the *DIC* measure to evaluate the behavior of each seller agent, the process takes into consideration both, the concession of the seller agents and the concession of their counterpart delegates. In some cases, the buyer's delegates may behave differently in terms of the amount of the concessions they are offering. Taking the behavior of a counterpart delegate into consideration to evaluate its opponent seller agent is important to reach an agreement. For example, if a delegate is playing tough in comparison to the other delegates and the opponent of that delegate is offering more concessions than the concessions offered by the delegate but less in comparison to the other seller agents' concessions, then the delegate may have a slight chance of reaching an agreement if the coordination mechanism does not consider the situation.

Ranking the seller agents according to their concessions is a possible way to compare their behaviors, however, the problem is that ranking the seller agents can be of little help in deciding the proper amount of concession that should be offered to each. To relate the concession offered by each opponent to the concessions offered by other opponents, the normalization process of dividing the concession offered by each seller agent by the total concessions offered by all seller agents provide a good overview of the concession of each seller agent in relation to the concessions offered by other agents. The normalization process also helps in automating the process of generating counteroffers for the next negotiation round, see Algorithm 1.

The proposed model uses the first-order differences of each agent's offers during the current negotiation for the first measure, while it uses the utility of the last offers received for the second measure. The function $u(x^t_{s_i \to d_i}[j]) = (max^b - x^t_{s_i \to d_i}[j])/(max^b - min^b)$ is used to calculate the utility of a received offer, $x^t_{s_i \to d_i}[j]$ is the offer from a seller s_i to a buyer's thread d_i at time t, min^b and max^b are the reservation intervals of the buyer agent's negotiation issue. Since agents are negotiating over a single issue, j rather than j_l (see Section 3.2) is used in this chapter to refer to the negotiation issue.

Algorithm 1 (β**C**)

Require: $X^{t-1}_{\mathbb{d}_i \leftrightarrow \mathbb{s}_i}[j], i = 1, 2, ..., n$
for $(i = 1 \to n)$ **do**
  $extract(X^{t-1}_{\mathbb{d}_i \to \mathbb{s}_i}[j]))$
  $extract(X^{t-1}_{\mathbb{s}_i \to \mathbb{d}_i}[j])$
end for
for $(i = 1 \to n)$ **do** ▷ cf. Section 4.3
  $\Delta s_i = (x^{t-1}_{\mathbb{s}_i \to \mathbb{s}_i}[j] - x^{t-2}_{\mathbb{s}_i \to \mathbb{s}_i}[j]), ..., (x^1_{\mathbb{s}_i \to \mathbb{s}_i}[j] - x^0_{\mathbb{s}_i \to \mathbb{s}_i}[j])$
  $\Delta d_i = (x^{t-1}_{\mathbb{d}_i \to \mathbb{d}_i}[j] - x^{t-2}_{\mathbb{d}_i \to \mathbb{d}_i}[j]), ..., (x^1_{\mathbb{d}_i \to \mathbb{d}_i}[j] - x^0_{\mathbb{d}_i \to \mathbb{d}_i}[j])$
end for
for (i=1 $\to$ n) **do**
  $\Delta F_i = \Delta s_i - \Delta d_i$
end for
$\Delta F = < \Delta F_1, \Delta F_2, ..., \Delta F_n >$
$F^{(t_1,t_2)}_j = select(t_1, t_2, \Delta F)$
$v_c = normalize(F^{(t_1,t_2)}_j)$
$Lu^t = u(X^{t-1}_S[j])$
$v_u = normalize(Lu^t)$
for $(i = 1 \to n)$ **do**
  $\psi^t_i = (1 - \gamma)v_c(i) + \gamma v_u(i)$ ▷ $\gamma \in [0, 1]$
end for
for $(i = 1 \to n)$ **do**
  $\beta^t_i = f_{\beta_i}(\psi^t_i)$
end for
$\mathrm{V}_{\beta^t} = \{\beta^t_i\}^n_{i=1}$
Return (V_{β^t})
end algorithm

Algorithm 1 (time complexity equals $O(n)$) summarizes the main steps of the algorithm β coordination, β**C**. It evaluates the behavior of each seller agent relative to its competitor seller agents' behaviors at the current time t and determines the convexity of the concession curve for each delegate accordingly. The β**C** strategy is executed at the start of each negotiation round. Steps 1 to 13 in Algorithm 1 represent the data preparation phase (see Section 4.3) that is necessary for the coordination process and it is done at the start of every negotiation round. Steps 14 normalize the vector $F_j^{(t_1,t_2)}$. The Lu^t in line 15 in Algorithm 1 stands for the utility vector of the last offers. The symbol $X_S^{(t-1)}[j]$ stands for the vector of the last offers received from the seller agents in-negotiation at time $(t-1)$ over the issue j. The lines *17-19* find a value for each seller agent represented by either v_c or v_u ($v_c, v_u \in [0,1]$). The value of γ is determined according to the importance of each measure. Steps 2 and 3 in Algorithm 1 are similar to steps 1 and 7 in example 4.1 respectively. Steps 6 and 7 in Algorithm 1 are similar to steps 2 and 8 in Example 4.1 respectively. Step 13 in Algorithm 1 is similar to step 17 in Example 4.1. The final output of the algorithm is the vector V_{β^t} that has a new β for each delegate.

A seller agent s_i with $v_c^t(i) = 0$ indicates that s_i is the most unfavorable agent in terms of its relative concession at time t, whereas $v_c^t(i) = 1$ indicates that s_i is the most favorable seller agent in terms of the amount of its relative concession at the current time t. Accordingly, values near 1 indicate favorable seller agents and values near 0 indicate unfavorable seller agents. The same interpretation applies to the vector v_u.

The function $f_{\beta_i}(.)$ (line 21 in Algorithm 1) is realized in Equation 5.1. The output of the function $f_{\beta_i}(.)$, β_i^t, is assigned to the delegate d_i at time t. The delegate d_i uses β_i^t to generate a counteroffer to be sent to the seller agent s_i at time t.

$$f_{\beta_i}(\psi_i^t) = \begin{cases} \mathbb{c} - \mathbb{c}\psi_i^t, & \psi_i^t \in [0, 0.5) \\ max[1-\psi_i^t, \rho], & \psi_i^t \in [0.5, 1] \end{cases} \tag{5.1}$$

At the start of negotiation, the buyer agent decides the maximum β it can use during negotiation and assign it to $\mathbb{c}$. For example, in our experiments, we use $\mathbb{c} \in [1, 2]$. For example, if $\psi_i^t = 0.4$, then $\beta_i^t = 2 - 2 * 0.4 = 1.2$. When $\beta = 1.2$, the buyer agent concedes more than when $\beta = 0.5$, for example. If $\psi_i^t = 0.7$, it means that the opponent is behaving favorably, then $\beta_i^t = max[1 - 0.7, 0.2] = 0.3$. A 0.3 β

value indicates that the delegate d_i is offering little concession at time t. The value of the $\mathbb{c}$ has a significant effect on both, the utility rate and agreement rate. When the situation is favorable to the buyer agent, the value of the $\mathbb{c}$ should be selected to be small (e.g., 1 or less) to secure a high utility rate, otherwise, the value of $\mathbb{c}$ should be higher to guarantee an agreement. The ρ value determines the minimum β_i at time t when $\psi_i^t = 1$. The value of ρ in the experiments is 0.1.

It is obvious from Equation 5.1 that the strategy choice exploits the situation and works like a greedy algorithm. In addition, it considers both, maximizing the utility gain of an agreement and maximizing the total number of agreements. The buyer agent chooses to play tough with lenient opponents while playing lenient with tough opponents, see Section 4.3. This decision reflects the buyer agent's belief about the social behavior of the seller agents. If the buyer has a different belief, the strategy updating mechanism may change.

5.2.2 Experimental Results and Discussion

To evaluate the proposed β**C** coordination mechanism, different negotiation environments are designed to evaluate the performance of the proposed mechanism. In the first set of experiments, the buyer agent is assumed to have the privilege of reneging from an agreement without incurring a penalty, see Section 2.5.1. Unless stated to the contrary, the seller agents use the (*MTD*) tactic (see Section 4.5.2) to generate their offers.

The proposed strategy are benchmarked against four other strategies, namely, the desperate strategy (*DE*), the patient strategy (*PA*), the optimized patient strategy (*OP*) that are proposed in [115] and the (*eCN*) strategy that is proposed in [106]. The *eCN* uses historical data from previous negotiations and changes the negotiation strategy of a buyer's delegate after the corresponding opponent agent has been classified either as a conceder or a non-conceder. The *DE* buyer agent accepts the first acceptable offer and quits negotiation while the *PA* agent stays in negotiation until it reaches its deadline then it selects the agreement with the highest utility, hence it does need to pay penalty for reneging from all other temporary agreements. The *OP* buyer agent changes its bidding strategy by changing its reservation value during negotiation. Once the *OP* agent reaches a temporary agreement, it announces its new reservation value to all of its delegates since it will not accept any offer worse than the one it already has. Finally, the *eCN* and the β**C** buyers change the convexity (by changing the β value) of their concession curve during negotiation.

The buyer agents' settings: five different buyer agents are being tested. Each buyer uses a different negotiation strategy, the strategies are: β**C**, *eCN*, *DE*, *PA* and *OP*. All buyer agents use the same initial settings including the deadline, the β value and the reservation interval. In most experiments, one β value is selected randomly from the same interval and assigned to all buyer agents. All buyer agents use the polynomial function when adopting the time-dependent tactics to generate their counteroffers.

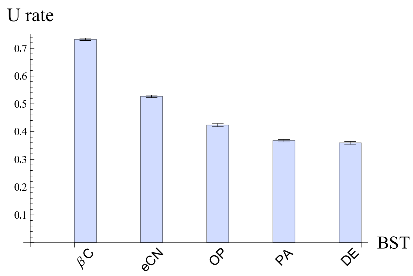
The minimum and the maximum values of the reservation interval of the buyer agents are generated at the start of every negotiation instance. The minimum value is selected randomly from the interval $[5, 10]$ whereas the maximum value is selected randomly from the interval $[30, 50]$. A negotiation instance refers to all the negotiation rounds determined by the deadline. The end of a negotiation instance is marked by an agent either accepting a proposal or quiting negotiation.

The seller agents' settings: at the start of each negotiation instance, each seller agent selects a random β value from the interval $[0.5, 10]$. Unless stated to the contrary, an overlap percentage (Φ_j) is selected randomly from the interval $[0, 1]$ for each seller agent to determine the length of the overlap (agreement zone) between its reservation interval and the reservation interval of its delegate counterpart, then the reservation intervals are computed according to Equation 4.4.

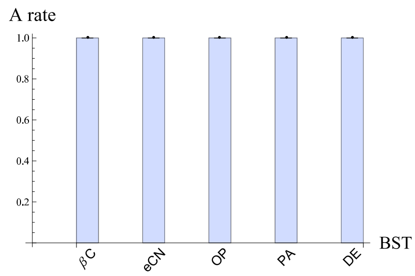
In each negotiation instance, new five seller agents are created with different negotiation parameters. All buyer agents negotiate with the same five seller agents concurrently. More specific negotiation settings for the buyer and the seller agents are stated according to the objective(s) of the experiments in the following sections. Each experiment is repeated 1000 times (encounters) for each buyer agent and the results are averaged and plotted. The Mann-Whitney test [85] is used to ensure that the difference between the β**C** and the best existing strategy is significant at 95% confidence level. In addition, the error bars are shown.

5.2.2.1 Testing under Different Deadline Lengths

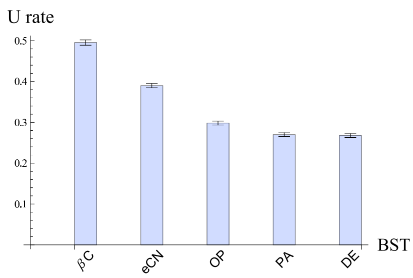
This section tests the proposed bidding strategy under different deadline lengths: When all agents (buyer and seller agents) have the same deadline, when the buyer agents have shorter deadlines than their counterpart seller agents' deadlines and when the buyer agents have longer deadlines. The deadline intervals that are used in this section are $[5, 30]$ and $[31, 50]$. When all agents use equal deadlines, a random deadline is selected in every negotiation instance from the interval $[5, 30]$ and assigned to all agents. When the buyer agents use shorter deadlines, a random deadline is selected in every negotiation instance from the interval $[5, 30]$ and assigned to all buyer agents, whereas each seller agent selects a random deadline from the interval $[31, 50]$. Finally, when the buyer agents use longer deadlines, a deadline is selected randomly from the interval $[31, 50]$ at the start of every negotiation instance and assigned to the buyer agents, while each seller agent selects a deadline randomly from the interval $[5, 30]$.



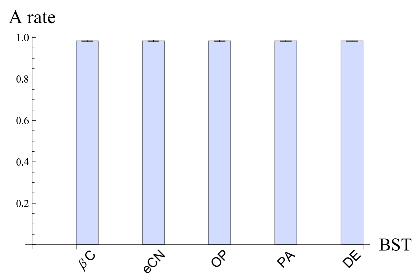
(a) Equal deadlines



(b) Equal deadlines



(c) Buyer's deadline is lower



(d) Buyer's deadline is lower

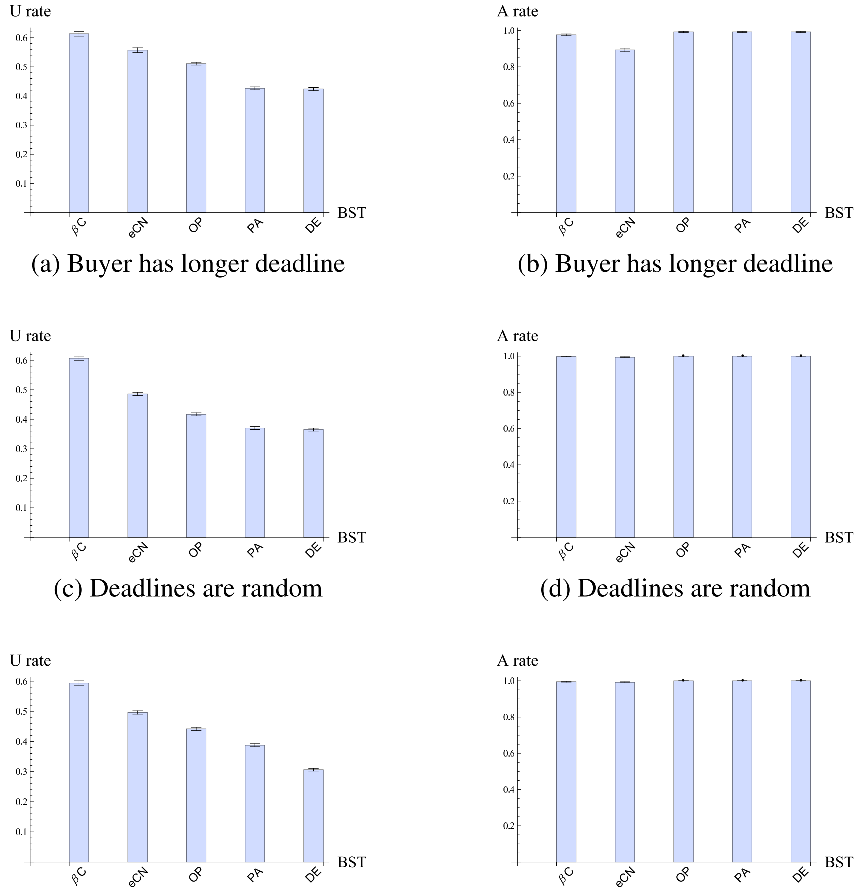
Figure 5.3: *The effect of equal and shorter deadlines on the performance of different bidding strategies.*

Figure 5.3 shows the results of using equal deadlines for all agents (Figures 5.3a and 5.3b) and using shorter deadlines (Figures 5.3c and 5.3d) for the buyer agents. In all figures, *A rate*, *U rate* and *BST* stand for the agreement rate, the utility rate and the buyer strategy, respectively. As Figure 5.3b shows, when all agents have the same deadline, the agreements rate is 100% for all strategies. The reason is that all agents offer their reservation values at their deadlines and since the agreement zones exist between all agents, reaching an agreement is definite. When the buyer agents have shorter deadlines, all achieve slightly lower agreement rates than in the previous case. However, all agents achieve the same agreement rate, see Figure 5.3d. The reason is that all buyer agents offer their reservation values (which are the same for all buyer agents) at their deadlines and this results in achieving the same agreement rate.

Figures 5.3a and 5.3c show that the proposed β**C** strategy outperforms all other strategies significantly in terms of the utility rate when the buyer agents and the seller agents have equal deadlines and when the buyer agents have shorter deadlines. The *eCN* outperforms the strategies *OP*, *PA* and *DE* significantly in terms of utility rate. The results for the *OP* strategy is as expected. Since the *OP* buyer adjusts its reservation value after reaching the first agreement, it is expected to reach an agreement with a higher utility in the following negotiation rounds. Since the strategies *DE* and *PA* use the same β value and do not change any of their negotiation parameters during negotiation, the difference between them is not significant in terms of a utility rate. In case the buyer agents use five different β values, the difference between the *DE* and the *PA* can be spotted as shown in Figure 5.4.

When the buyer agents have shorter deadlines, they achieve lower utility rates than the case when all agents have equal deadlines. The reason is that the buyer agents offer their reservation values at their deadlines which means they offer their reservation values before the seller agents do. However, the β**C** strategy outperforms all other strategies significantly in terms of utility rate when the buyer agents have shorter deadlines, see Figure 5.3c.

Figure 5.4 shows the results of testing the buyer agents' strategies when the buyers have longer deadlines, and when the deadlines are selected randomly for all agents. In addition, the figure shows the results of an experiment when the buyer agents use five different β values selected from the interval $[0.5, 10]$ at the start of each negotiation round. In the experiment, the same five β values are assigned to the buyer agents. The experiment is conducted to test the difference between the *DE* and the *PA* strategies un-



(a) Buyer has longer deadline

(b) Buyer has longer deadline

(c) Deadlines are random

(d) Deadlines are random

(e) Deadlines are random with different β values

(f) Deadlines are random with different β values

Figure 5.4: *The effect of longer deadlines and randomly selected deadlines on the performance of different bidding strategies.*

der different settings since the previous experiments did not show a difference between the two strategies.

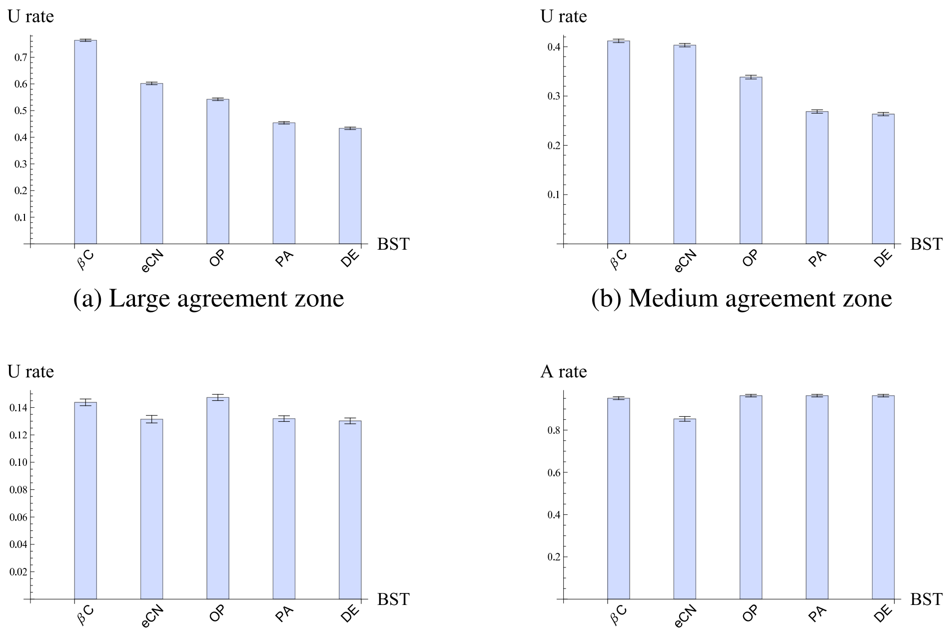
It seems that longer buyer deadlines are disadvantageous (see Figure 7.4) to the *eCN* in terms of an agreement rate. The reason is that the *eCN* strategy classifies the seller agents according to their concessions into either a conceder or a non-conceder and computes the β value for each group differently. If all seller agents are classified into one group, then they will have the same β value which makes the strategy more rigid. On the other hand, the β**C** strategy assigns a possibly different β value to each delegate according to the behavior of its counterpart seller agent which reduces the chances of missing an agreement in difficult negotiation environments. To rectify this problem, the *eCN* buyer agent needs to postpone applying its strategy until it secures the first agreement as the *OP* does. Both, the β**C** and *eCN* strategies can be used on the top of the *OP* strategy to improve both, the agreement rate and the utility rate.

Figures 7.3, 7.5 and 7.7 show that the results are consistent in terms of utility rate where the β**C** strategy outperforms all other benchmark strategies. The agreement rate for all buyer agents are similar when random deadlines are used, see Figures 7.6 and 7.8. The reason is that each buyer agent negotiates with five seller agents of different deadlines which improves the chance of reaching an agreement between a buyer agent and one of the five seller agents.

5.2.2.2 Testing Under Different Reservation Interval Overlaps

This section tests the proposed bidding strategy under three different agreement zone lengths: small, medium and large. The length of an agreement zone is determined the by value of Φ_j, see Equation 4.4. In all the experiments of this section, different types of buyer agents use the same deadline selected randomly from the interval $[5, 30]$ and each seller agent selects a random deadline from the same interval, i.e., $[5, 30]$. All seller agents use the *MTD* tactic to generate their offers.

Figure 5.5 shows the results of testing different negotiation strategies under three overlaps: small, medium and large. For small overlaps, each seller agent selects a random Φ_j value from the interval $[0.7, 0.9]$. The intervals for the medium and the large overlaps are $[0.4, 0.6]$ and $[0, 0.3]$ respectively. Figure 5.5a shows that the β**C** strategy achieves a higher utility rate in comparison to the other strategies when the agreement zones between agents are large, i.e., large overlap between the reservation intervals of agents. All different buyer agents achieve almost 100% agreement rate when the agreement zone length is large or medium, figures are not shown. The strategy β**C** achieves a similar or better utility rate (the *p-value*$_{(\beta\mathbf{C},eCN)}$*=0.04<0.05* in Figure 5.5b) than the *eCN* startegy when the length of the agreement zone is medium, see Figure 5.5b. Small agreement zone lengths have a negative effect on the performance of all strategies, see the utility rates of Figures 5.5a and 5.5c. The reason is that an agent needs to approach its reservation value to achieve an agreement. However, the *eCN* is the most affected amongst all strategies for the reasons stated in Section 5.2.2.1. In figures 5.5c and 5.5d, the differences between the strategies β**C** and *OP* are not statis-



(a) Large agreement zone

(b) Medium agreement zone

(c) Small agreement zone

(d) Small agreement zone

Figure 5.5: *The effect of different overlap percentages on the performance of different bidding strategies.*

tically significant (*p-value* > *0.05*) in terms of both utility rate and agreement rate. The strategies β**C** and *eCN* can be used on the top of the *OP* strategy, a buyer agent can apply either the β**C** strategy or the *eCN* strategy after the first agreement is achieved to improve both, the agreement rate and the utility rate.

5.2.2.3 Testing under Other Negotiation Environmental Conditions

In all the above experiments shown in sections 5.2.2.1 and 5.2.2.2, the buyer agents are given the opportunity to renege from an agreement without paying penalties. However, in many real situations, either an agent needs to honor its agreement or pay a penalty when reneging from an agreement. To test the performance of the β**C** strategy under the condition where a buyer agent needs to honor its first agreement, experiments are conducted to test three different strategies under random deadlines and random overlaps. The *PA* and the *OP* strategies do not apply in this case. The strategies *PA* and *OP* assume that a buyer agent has the privilege of reneging on an agreement(s) without paying penalty.

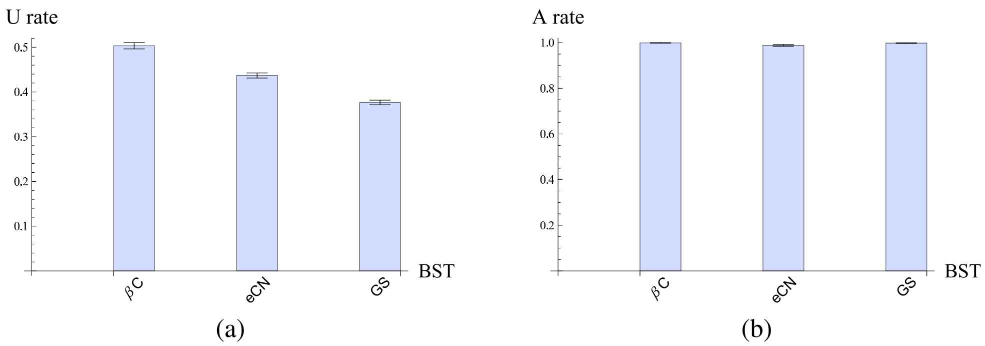
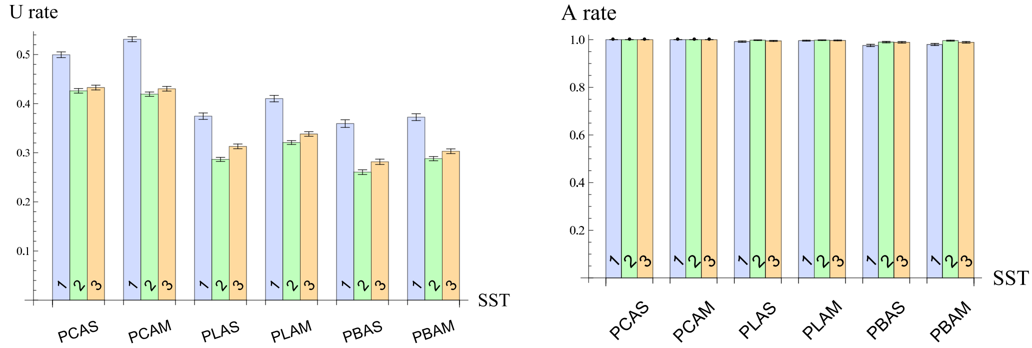


Figure 5.6: *The effect of selecting random deadlines and random overlaps on the performance of different bidding strategies when agents must honor their agreements.*

The three tested strategies are the β**C** strategy, the *eCN* strategy and the general strategy (*GS*). The *GS* strategy refers to the strategy where an agent assigns different values to the negotiation strategy parameters at the start of negotiation and does not change any of them during negotiation. Figure 5.6 shows the results of the experiments. Each buyer agent negotiates with the same five seller agents as before. The experiment is repeated 1000 times for each agent. The results are averaged and plotted. Figure 5.6a shows that the β**C** outperforms both, the *eCN* and *GS* strategies in terms of utility rate. All strategies have the same performance in terms of agreement rate. In general, buyer agents in the **SSM** coordination scenario do not have a serious problem in reaching an agreement if the length of the agreement zone between agents are long enough and the difference between their deadlines is not large. In addition, a buyer agent who negotiates with a large number of seller agents has a high chance of reaching an agreement.

To test the performance of the proposed strategy against different types of seller agents who use a strategy that mixes between the time-dependent and the behavior-dependent tactics to generate their offers, an experiment is designed to test three different buyers against six types of seller agents using mixing strategies. The notations of the seller agents' strategies shown in Figure 5.7 are explained in Section 4.5.2.

The experiment is repeated 1000 times for each category of seller agents. For example, to test the three buyer types (i.e., the β**C** agent, the *eCN* agent and the *GS* agent) against the seller agents of type *PCAS*, the three buyers negotiate 1000 times with five seller agents of type *PCAS*. In each negotiation instance, five seller agents are generated



(a) (b)

$(1 \rightarrow \beta\mathbf{C}, 2 \rightarrow eCN, 3 \rightarrow GS)$

Figure 5.7: *Seller agents mix between the time-dependent and the behavior-dependent tactics where all agents need to honor their agreements.*

randomly from the *PCAS* category and the three buyer types negotiate with the same five agents. The results are averaged and plotted. Random deadlines and overlaps are used at the start of each negotiation instance. All buyer agents have the same deadline in every negotiation instance. Finally, a β value is selected randomly from the interval $[0.5, 10]$ and assigned to the three buyer agents. The same process is repeated for the rest of the five categories of the seller agents.

Figure 5.7b shows that the three different buyer types record similar agreement rates. On the other hand, the $\beta\mathbf{C}$ strategy outperforms (with significant statistical difference) the other two strategies in terms of the utility rate in all cases, see Figure 5.7a. When the seller agents are selected from the *PCAS* and the *PCAM* categories, all buyer agent types achieve lower utility rates than the utility rates achieved when the buyer agents negotiate against the seller agents of the types *PLAS*, *PLAM*, *PBAS*, and *PBAM*. The reason is that the seller agents in the *PCAS* and the *PCAM* categories are time-dependent conceder types and since the contribution of the behavior-dependent is small to medium (see Section 4.5.2), the sellers are conceding quickly which means that the buyer agents reach agreements with higher utility rates. The experiments that consider testing the different negotiation strategies against sellers using mixing strategies prove that the proposed $\beta\mathbf{C}$ strategy is a dynamic strategy that responds to different negotiation environments and different opponent types in an effective and robust manner.

5.2.3 Testing Different Strategy Metrics

This section investigates the effect of both, the *DIC* and *LOU* measures on the performance of the β**C** strategy, see Section 4.3. Five different types of β**C** is designed and tested. Table 5.1 shows the five β**C** strategy variants determined by the *DIC* and the *LOU* measures. In Table 5.1, *RC* means that β**C** uses only the recent concessions as the only metric, the *TC* means that the β**C** uses the total concession to evaluate an opponent. Total concession means that the buyer agent considers all concessions of a seller agent since the start of negotiation. *LU* means the utility of the last offer is considered, i.e., the *LOU* measure. *RU* indicates that both, the *RC* and *LU* is considered with equal weights. Finally, the *TU* means that both, the *TC* and *LU* are used with equal weights. In all the experiments regarding testing different evaluation metrics, all buyer agents use the same deadline (randomly selected) in each negotiation round. In each negotiation instance, the five buyers using the five strategy variants negotiate with same five seller agents. At the start of each negotiation instance, new five seller agents are generated. Random deadlines and random overlaps are considered, see Section 5.2.2.1. In addition the used $\mathbb{c}$ value is equal to 2, see Equation 5.1. When two measures are used, each contributes 50% of the total evaluation of each opponent, see Table 5.1. As before, the number of repetitions for each experiments is 1000 times, see Section 5.2.2.3.

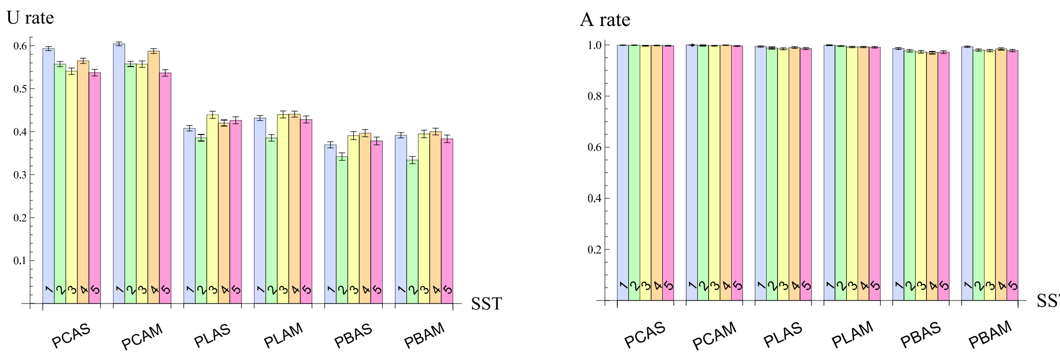
Table 5.1: *Different βC strategy variants*

		*R*ecent *C*oncession	*T*otal *C*oncession	*L*ast offer's *U*tility
β**C**	*RC*	✓	×	×
	TC	×	✓	×
	LU	×	×	✓
	RU	✓(50%)	×	✓(50%)
	TU	×	✓(50%)	✓(50%)

Figure 5.8 shows the experimental evaluation results of the five different β**C** strategy variants presented in Table 5.1. The β**C** strategy variants shown in Table 5.1 are created to test the effect of using the *DIC* and the *LOU* metrics on the performance of the β**C** strategy. In the first set of experiments, the five buyer types (named *RC, TC, LU, RU, TU*) played against seller agents who mix between the time-dependent and the behavior-dependent tactics to generate offers. The results in Figure 5.8a show that us-

ing the recent concessions *RC* metric to evaluate an opponent produces the best utility rates amongst all other variants when the seller agents are in the categories *PCAS* and *PCAM*. In the categories *PLAM* and *PBAM*, the variants *RC*, *LU*, *RU* and *TU* perform similarly since the difference amongst them are not significant. The *LU* variants outperformed all other variants when the seller agents are in the *PLAS* category, whereas the *TU* is the second best. The *TC* performance is the worse against most seller agents' categories. The *RC* does not perform well when the seller agents are in the categories *PLAS* and *PBAS*. The performance of the *RU* is second to best against the seller agents in the categories *PCAS* and *PCAM*.

In summary, the variant *RC* outperformed other categories when the seller agents used the mixing strategy to generate their offers. The *RC* variant produced the highest utility rate or is amongst those variants who produced the highest utility rates in four out of six seller agents' categories and performed better than all other variants in two out of six seller agents' categories.

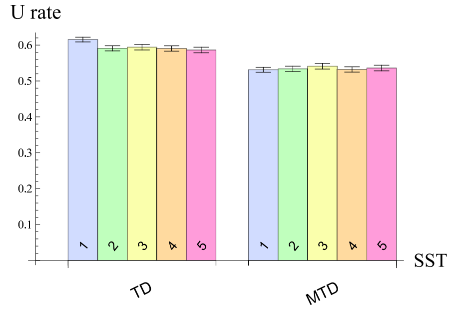


(a) (b)

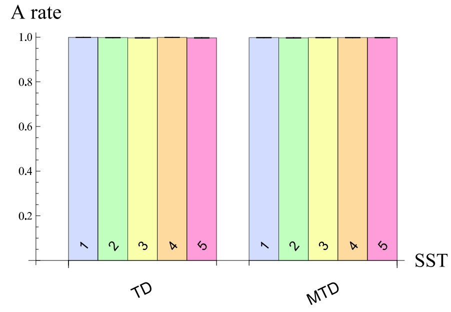
$$(1 \rightarrow RC, 2 \rightarrow TC, 3 \rightarrow LU, 4 \rightarrow RU, 5 \rightarrow TU)$$

Figure 5.8: *Seller agents mix between the time-dependent and the behavior-dependent tactics to generate their offers given that all agents must honor their agreements.*

To test the *DIC* and the *LOU* metrics in case the buyer agents are negotiating against seller agents using the time-dependent tactics to generate their offers, an experiment is designed to test the different β**C** strategy variants (see Table 5.1) against two categories of seller agents. The first category is the time-dependent (*TD*) tactics where each seller agent selects a β value randomly from the interval $[0.5, 10]$. The second category of the seller agents is when seller agents use the *MTD* tactics to generate their offers, see



(a)



(b)

$(1 \rightarrow RC, 2 \rightarrow TC, 3 \rightarrow LU, 4 \rightarrow RU, 5 \rightarrow TU)$

Figure 5.9: *Seller agents who use the time-dependent and the MTD tactics to generate their offers given that all agents must honor their agreements.*

Section 4.5.2. In each experiment, five seller agents are generated from a certain category and each of the five buyer agent variants (see Table 5.1) negotiates with the same five seller agents. Deadlines and overlaps are selected randomly as in the previous experiments where all the five buyer agents have the same deadline, selected randomly - as before - at the start of each negotiation instance.

The results of the experiments are shown in Figure 5.9. Figure 5.9b shows that all types of buyer agent variants are similar with regards to the agreement rate. However, *the utility rate results show some variation*, see Figure 5.9a. There are three main observations in Figure 5.9a: the first one is that all buyer types achieve more utility rate when negotiating against the *TD* agents than when negotiating against the *MTD* agents. The reason is that the *TD* agents have a higher chance to receive a higher β value than the β value received by the *MTD* agents. The agents using the *MTD* receive a β value calculated as a weighted average of the three main types of the time-dependent tactics (i.e., conceder, linear and Boulware) which moderates the β value and makes it in a less conceding range, see Section 4.5.2. The second observation is that all buyer types have similar performance against the *TD* seller agents. As mentioned before the *TD* agents selects their β value from the interval $[0.5, 10]$. Most of the interval length represents the conceder behavior (when $\beta > 1$) which means most of the randomly selected β values define conceder agent types. A conceder agent offers large concessions at the start of negotiation which results in achieving agreements with high utility from the buyer agents' side. In addition, the conceding behavior of the seller agent results in similar utility rates achieved by the different buyer variants.

The third observation is that when the buyer agent variants negotiate against the *TD*, the *RC* performs better than the other variables while if the seller agents are of type *MTD*, all buyer variants perform similarly.

In most cases, the *RC* metric is proved to be a better evaluation criterion than the *TC* metric. The total concessions for two agents can be the same at a certain point in time during negotiation even if the two agents are offering different amounts of concessions at different times. For example, assume that agents a_1 and a_2 are in negotiation and agent a_1 concedes 2 units every round and agent a_2 concedes 1 unit every round. After 9 negotiation rounds, the total amount of concessions of agent a_1 is 18 units and the total amounts of concessions of agent a_2 is 9 units. At the next negotiation round, agent a_1 concedes 2 units and agent a_2 concedes 11 units. The two agents offered the same amount of concession in total in the negotiation round number 10. It can be guessed that agent a_2 is more desperate to reach an agreement than a_1. In addition, the recent concession metric is proved to be similar or better than the utility metric in most cases. The reason is that the utility measures the current value of an opponent agent without considering its previous behavior in terms of the concession offered. The recent concession considers the most recent behaviors of all agents which can evaluate them more accurately.

Even though the *RU* metric is used in the experiments of Section 5.2.2, the *RU* metric performs better than all other benchmark strategies. In the future experiments, the *RC* metric will be considered.

5.3 MSM Coordination Scenario

This section presents coordination mechanisms that are designed to coordinate the bidding strategy for the **MSM** coordination scenario where a buyer agent is negotiating with seller agents over multiple distinct objects given that each object has a single negotiation issue and multiple providers, see Figure 5.10.

Procuring more than one negotiation object is a daily practice of buyers who use either physical stores or virtual stores. We investigate the situation where a buyer agent is negotiating with multiple seller agents concurrently for the purpose of reaching multiple agreements over multiple objects, i.e., one agreement per one object. For example, in *service composition*, a buyer agent may negotiate over multiple distinct services where each service has multiple providers.

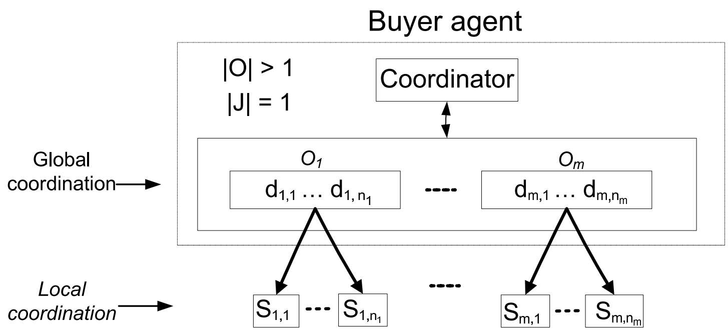


Figure 5.10: *One-to-many negotiation over multiple negotiation objects of one issue*

There are two levels of coordination shown in Figure 5.10. The first level is referred to as *global coordination* while the second one is called *local coordination*. The global coordination considers the overall situation of negotiation taking into consideration the common factor(s) in the given coordination scenario. There are two common factors in our scenario: the first one is that all objects have the same issue, i.e., the negotiation issue is common amongst all objects, e.g., price. The second factor is that the agreements are *connected*. Thus if a negotiation over an object results in failure regarding any object, the whole negotiation process fails.

The local coordination indicates that the coordination mechanism(s) considers the negotiation situation with regards to a certain object without considering the negotiation situation of other objects. The proposed coordination mechanism considers the number and behaviors of the seller agents of a certain object in terms of their concessions in comparison to the concessions offered by their counterpart delegates. In all coordination mechanisms proposed in this thesis, only those sellers that are still negotiating are considered. If a seller quits negotiation, it is dropped from the analysis process.

This section presents three coordination mechanisms classified according to the coordination scope: a global **MSM** mechanism (**GMSM**), a local **MSM** mechanism (**LMSM**) and finally a hybrid (**MSM**) mechanism (**HMSM**). In all the experimental results shown in this section, all agents honor their first agreement. Unless stated to the contrary, all seller agents use the *MTD* tactic to generate their offers.

5.3.1 Global MSM Strategy

The proposed global negotiation strategy considers assignment of possibly new local reservation values (see Section 4.4) to the negotiation issue(s) in each negotiation round. The assignment of a new local reservation value for each negotiation issue of each object depends on both the values of consecutive offers received from each provider of each object and their counterpart delegates' consecutive counteroffers. Algorithm 2 summarizes the main steps of the **GMSM** mechanism. Each object is assigned a weight that determines its issue's local reservation value. For example, if the weight vector for four objects is $\mathbb{w} = \{0.3, 0.2, 0.4, 0.1\}$ and the global reservation value is \$100, then the local reservation values are $\{30, 20, 40, 10\}$. The initial weight vector is assigned based either on domain knowledge or previous negotiation experience.

The lines *1-5* in Algorithm 2 assign a zero weight for each procured object and then recompute the weights for the remaining objects in line 6. The data preparation process presented in lines *7-13* is similar to the data preparation process shown in Algorithm 1. The difference is that the data process of Algorithm 1 considers one negotiation object while the data preparation process shown in Algorithm 2 considers multiple objects and m in the algorithm stands for the number of negotiation objects required by the buyer agent, see Figure 5.10. Line 14 computes the mean vector for the vector $F_j^{(t_1,t_2)}$ (see Section 4.3) while line 15 normalizes the mean vector that results in relating the behaviors of the seller agent groups to each other by dividing the value of each member in the vector by the sum of the vector. The normalization process in the given context provides a value for each group of seller agents relative to the other seller agent groups.

An example of the vector $F_j^{(t_1,t_2)}$, $F_j^{(t_1,t_2)}$=< *<1,2,3>,<-1,0,3>,<2,4>,<5>* >. In this case, the number of the required objects is 4. The element *<1,2,3>* represents the difference between the first order differences of the concessions offered by the providers and the concessions offered by their counterpart delegates in the previous negotiation round over the negotiation issue j of object 1.

The element $< 2, 4 >$ represents the same information for two pairs of agents which indicates that one of the object 3 providers withdrew from negotiation and only two providers are left. For object number 4, there is only one provider left.

Algorithm 2 GMSM algorithm

Require: *global reservation value*, $\mathbb{g}$
Require: *local reservation value weight vector*, $\mathbb{w}$
Require: $< X^{t-1}_{\mathbb{d}_{1,1}\leftrightarrow\mathbb{s}_{1,1}}[j], X^{t-1}_{\mathbb{d}_{1,2}\leftrightarrow\mathbb{s}_{1,2}}[j], ..., X^{t-1}_{\mathbb{d}_{1,\mathbb{n}_1}\leftrightarrow\mathbb{s}_{1,\mathbb{n}_1}}[j] >, ...,$
$< X^{t-1}_{\mathbb{d}_{\mathbb{m},1}\leftrightarrow\mathbb{s}_{\mathbb{m},1}}[j], X^{t-1}_{\mathbb{d}_{\mathbb{m},2}\leftrightarrow\mathbb{s}_{\mathbb{m},2}}[j], ..., X^{t-1}_{\mathbb{d}_{\mathbb{m},\mathbb{m}_\mathbb{n}}\leftrightarrow\mathbb{s}_{\mathbb{m},\mathbb{m}_\mathbb{n}}}[j] >$
1: **for** $k = 1 \to m$ **do**
2:     **if** $(isProcured(k))$ **then**
3:         $\mathbb{w}(k) = 0$
4:     **end if**
5: **end for**
6: $\mathbb{w} = \mathbb{w}/sum(\mathbb{w})$
7: **for** $i = 1 \to m$ **do**
8:     $\Delta\mathbb{d}_i =< \Delta\mathbb{d}_{i_1}, \Delta\mathbb{d}_{i_2}, ..., \Delta\mathbb{d}_{i_n} >$
9:     $\Delta\mathbb{s}_i =< \Delta\mathbb{s}_{i_1}, \Delta\mathbb{s}_{i_2}, ..., \Delta\mathbb{s}_{i_n} >$
10:     $\Delta F_i = \Delta\mathbb{s}_i - \Delta\mathbb{d}_i$
11: **end for**
12: $\Delta F = < \Delta F_1, \Delta F_2, ..., \Delta F_m >$
13: $F_j^{(t_1,t_2)} = select(t_1, t_2, \Delta F)$
14: $meanVec = mean(F_j^{(t_1,t_2)})$
15: $v_m = meanVec/sum(meanVec)$
16: $minMax = minMaxPairs(v_m)$
17: **for** $(i = 1 \to size(minMax))$ **do**
18:     $\varphi = minMax[i]$
19:     **if** $(max(F_j^{(t_1,t_2)}(\varphi[1]))) <= 0$ **then**
20:         **if** $(max(F_j^{(t_1,t_2)}(\varphi[2]))) > 0$ **then**
21:             $\mathbb{w}(\varphi[1]) = \mathbb{w}(\varphi[1]) + \mathbb{w}(\varphi[2]) * \gamma$ $\triangleright\ \gamma \in [0, 1]$
22:             $\mathbb{w}(\varphi[2]) = \mathbb{w}(\varphi[2]) - \mathbb{w}(\varphi[2]) * \gamma$
23:         **end if**
24:     **end if**
25: **end for**
26: $newLocalRes = \mathbb{g} * \mathbb{w}$
27: $Return(\mathbb{w}, newLocalRes)$
28: **end algorithm**

Line 16 shows the function $minMaxPairs(.)$ that takes the normalized mean vector v_m as a parameter and returns the vector $minMax$ that consists of elements of one *pair* each. Each pair contains two object positions. The object in the first position of every pair indicates a difficult negotiation situation for the delegates responsible for procuring that object while the object in the second position indicates a favorable negotiation situation for the delegates responsible for procuring the one in the second position. The algorithm $minMaxPairs(.)$ repeats $|v_m|/2$ iterations. For odd $|v_m|$ values, the number of iterations is $(|v_m| - 1)/2$. In each iteration, the positions of the minimum and the maximum values in the v_m vectors are joined in one pair. Once the two members are joined, they are excluded from the next iteration. For example, assume that $v_m =< 0.1, 0.2, 0.4, 0.3 >$, then the function $minMaxPairs(v_m)$ returns the vector $minMaxPairs(v_m) =< (1,3), (2,4) >$. The first pair $(1,3)$ ($\varphi = minMax[1] = (1,3)$) indicates that the buyers' delegate group in position 1 (i.e., the group responsible for procuring the object in position 1) in the vector v_m is negotiating with the toughest seller agents group and the seller agent group in position 3 are the most current favorable group. Now, there are only two groups left in which the seller agent group in position 2 is the toughest and the seller agent group in position 4 is the most favorable. The position numbers in the v_m vector refer to the objects: $o_1, o_2, ..., o_m$, see Figure 5.10. The **GMSM** negotiation strategy considers only the seller agents for the objects that are to procure yet.

The idea behind the algorithm $minMaxPairs(.)$ is to define a resource reallocation mechanism during concurrent negotiation on the bases of *need*. The aim is to locate the potential sources of resources and the possible targets for the redistribution of resources. Once the vector of pairs $minMax$ is determined according to the algorithm $minMaxPairs(.)$, a certain amount can be shifted from one local reservation value to another. Lines *17-25* in Algorithm 2 show the process of shifting resources between local reservation value weights given that some conditions exist. The process works as follows: for each pair in the vector $minMax$, see line 17, the algorithm checks if the maximum value in the vector $F_j^{(t_1,t_2)}(\varphi[1])$ of element i in the vector $minMax$ is less than zero, see line 19. If this is true, it indicates that the chance of reaching an agreement over the object in position $\varphi[1]$ is small. In this case, the process checks if the maximum value in the vector $F_j^{(t_1,t_2)}(\varphi[2])$ is greater than zero, see line 20; if so, it means that there is a chance for shifting some resources without jeopardizing an agreement over the object in the position $\varphi(2)$ of the element i in the vector $minMax$, see lines 21 and 22.

The $\varphi[1]$ stores one object position and $\varphi[2]$ stores its partner. In our previous example, when $i = 1, \varphi[1] = 1, \varphi[1] = 3$. In the previous example, $F_j^{(t_1,t_2)}(\varphi[1]) =< 2, 4 >$.

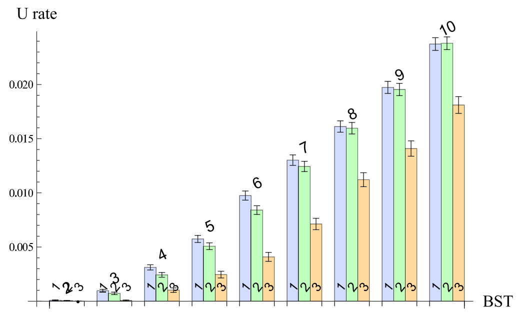
The value γ used in the experiments is $10 - 15\%$, see lines 21 and 22. The value of γ can be determined from the empirical evaluation or from prvious experience. To accomodate for the situations where the difference between the initial local reservation values are substatial, the mechanism needs to consider that by building a weight redistribution matrix between different negotiation issues to control the amount of resource shifting according to the values that relate issues to each other.

Having said that, and in the context of the described coordination scenario, the process of redistributing resources during negotiation is effective only under tough negotiation environments where the agreement zone lengths between the buyer and the seller agents are small. This condition applies to the proposed **GMSM** as well as to the *surplus redistribution* (*SR*) mechanism [118]. In addition to the general strategy (*GS*), the *SR* strategy is used as a benchmark for testing the proposed coordination mechanisms in this section. The *SR* is considered as a global strategy where it changes the local reservation values during negotiation.

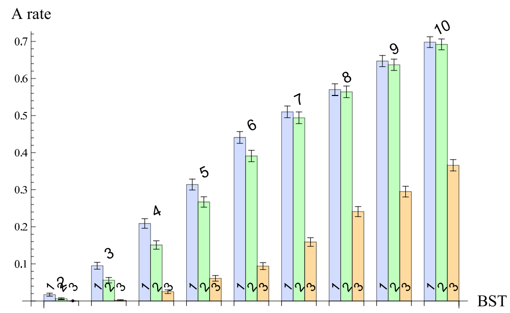
5.3.1.1 Experimental Results and Discussions

In the following experimental results, the first agent uses the proposed **GMSM** strategy, the second agent uses the *SR* strategy and the third agent uses *GS*. The *SR* waits until one or more objects is/are procured then it redistributes extra resources (if any) to the remaining delegate groups. For example, if the buyer agent is negotiating over 4 distinct objects and the local reservation value set for their issues is $\{60, 70, 80, 100\}$, then if during negotiation the delegate group responsible for procuring object number 1 is able to reach an agreement by paying only 54, then there are $\$6$ surplus which will be redistributed over the remaining delegate groups to help them reach agreements. The redistribution of the surplus could be even which means that each delegate group receives \$2 and the new local reservation value set becomes $\{0, 72, 82, 102\}$ or based on the weights of the objects. Since each object contains only one negotiation issue, the object's weight and the issue's weight are used interchangeably here. In the experiments, the surplus redistribution is performed according to the weights of the objects; the higher the weight, the higher the share. The weights of the objects for all buyer agents are determined according to their initial issues' local reservation values. Finally, *GS* establishes the various negotiation parameters (according to some domain knowledge or previous experience) and keeps those parameters unchanged throughout negotiation.

The specific negotiation settings for the results shown in Figures 5.11, 5.12 and 5.13 are as follows: in each negotiation round, all buyer agents use the same deadline that is selected randomly from the interval $[5, 30]$ and the same β value that is selected randomly from the interval $[0.5, 5]$. All buyer agents start with same local reservation values where the minimum value is selected randomly from the interval $[5, 10]$ and the maximum value is selected randomly from the interval $[40, 50]$ in every negotiation round. Each seller agent selects a random deadline from the same interval, i.e.,$[5, 30]$ and a random β value from the interval $[0.5, 10]$. In addition, the percentages of overlaps between the local reservation values of the agents' issue are selected randomly from the interval $[0.9, 1]$ which means that any overlap percentage will be $\%10$ or less, see Equation 4.4. Unless stated to the contrary, the number of negotiation objects used in the experiments of this section is 10.



(a)



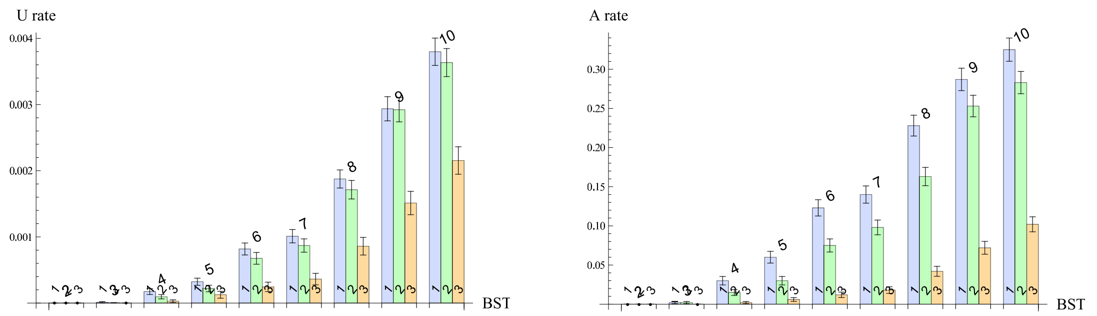
(b)

$(1 \rightarrow GMSM, 2 \rightarrow SR, 3 \rightarrow GS)$
(The numbers above the graph bars refer to the number of seller agents per object)

Figure 5.11: *Testing the strategies GMSM, SR and GS; number of seller agents varies*

The first experimental results are shown in Figure 5.11. The numbers above the *bars* in Figures 5.11 and 5.12 indicate the number of seller agents per object. For each distinct number of agents, the experiment is repeated 1000 times and the results are averaged and plotted. The experiment starts with 2 agents per object and the number increases until it reaches 10 seller agents per object. The results show that when the number of seller agents is relatively small, the proposed **GMSM** strategy outperforms the *SR* strategy significantly in terms of agreement rate and equal or better in terms of utility rate. Both, the **GMSM** and *SR* outperform *GS* significantly in all cases, see Figures 5.11a and 5.11b.

Anther set of experiments show that when the overlap percentages between the agents' reservation intervals are $\%5$ or less, the **GMSM** strategy proves to have even more significant performance than the *SR* strategy in terms of agreement rate, see Figure 5.12b. Figure 5.12a shows that the **GMSM** strategy performs better than the *SR* strategy in



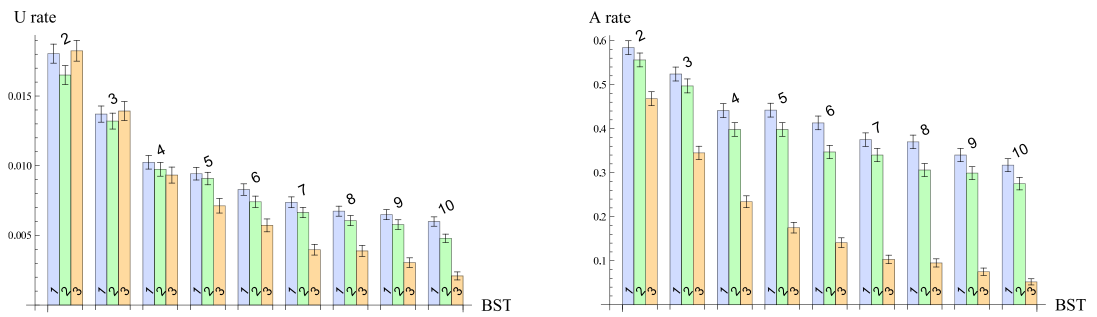
(a) (b)

$(1 \rightarrow GMSM, 2 \rightarrow SR, 3 \rightarrow GS)$
(The numbers above the graph bars refer to the number of seller agents per object)

Figure 5.12: *Testing the strategies GMSM, SR and GS; number of seller agents varies*

terms of utility rate. However, the *error bars* in Figure 5.12a show overlaps in most cases which means that the difference between the **GMSM** strategy and the *SR* strategy is statistically insignificant in terms of utility rate.

The **GMSM** strategy is a more dynamic one than the *SR* strategy since the *SR* waits until an agreement is reached over an object before it starts redistributing the extra resources, if they exist. The **GMSM** strategy does not wait until reaching an agreement to redistribute resources, it rather assesses the current situation and acts accordingly, see lines *17-25* in Algorithm 2.



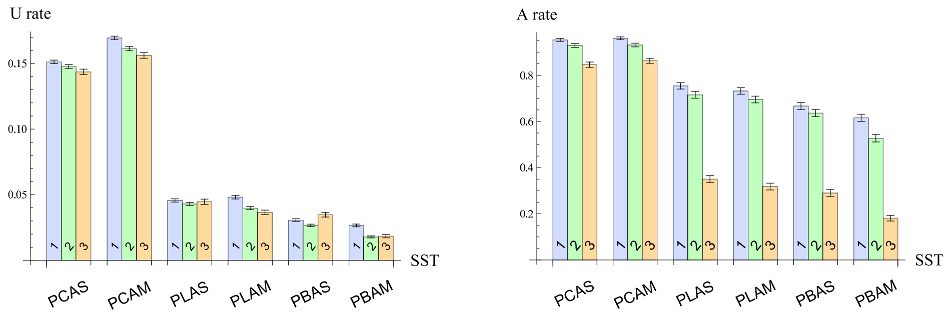
(a) (b)

$(1 \rightarrow GMSM, 2 \rightarrow SR, 3 \rightarrow GS)$
(The numbers above the graph bars refer to the number of negotiation objects)

Figure 5.13: *Testing the strategies GMSM, SR and GS; number of objects varies*

On the other hand, Figure 5.13 shows the experimental results for the three buyer agents negotiating against 5 seller agents over different number of objects. The numbers above the *bars* in the figure indicate the number of negotiation objects. The number starts with 2 distinct objects and increases up to 10 objects. When the number of objects increases, the **GMSM** strategy outperforms the other two strategies in terms of utility rate and agreement rate, see Figures 5.13a and 5.13b. Both dynamic strategies outperform *GS* in terms of utility rate and agreement rate when the number of objects becomes large. When the number of objects becomes large, it becomes difficult for all strategies to reach a large number of agreements. However, **GMSM** proved to be more effective than the *SR* strategy especially when the number of objects becomes large.

Figure 5.14 shows the experimental results when the three buyer agents are negotiating against seller agents who mix between the time-dependent tactics and the behavior-dependent tactics to generate their offers, see Section 4.5.2. In most cases, the **GMSM** outperforms the *SR* strategy in terms of utility rate and agreement rate, see Figures 5.14a and 5.14b. *GS* shows a better utility rate than the other two strategies in case the seller agents are selected from the type *PBAS*. The reason is that the seller agents in the type *PBAS* use the *Boulware tactic* to generate their offers which constitute large portion of their final mixed offers, while the contribution of the behavior-dependent strategy is small, see Section 4.5.2.



(a) (b)

($1 \rightarrow GMSM$, $2 \rightarrow SR$, $3 \rightarrow GS$)

Figure 5.14: *Testing the strategies GMSM, SR and GS; the seller agents mix between the time-dependent tactics and the behavior dependent tactics to generate their offers*

When all the seller agents are of Boulware type, they offer little concessions throughout negotiation until they approach their deadlines in which they offer large concessions. In this case and because the two dynamic strategies shift resources during negotiation, the utility of an agreement is expected to be low. Figure 5.14b shows that the two dynamic strategies outperform *GS* in terms of utility rate and significantly in all cases in terms of agreement rate. The percentage of overlaps used in the experiments of Figure 5.14 are selected randomly to be 30% or less. The rest of the experimental settings are the same as in the experiments used to generate the previous results in this section.

When the length of the agreement zone between agents is small, a small utility is expected for an agreement. The results of utility rate show this in all figures of this chapter, e.g., Figures 5.11, 5.12 and 5.13. The reason is that, since the overlap percentages between the reservation intervals of the buyer agents and the seller agents are small, all agents need to approach their reservation values before reaching the agreement zone which results in low utility rate outcomes for all agents.

5.3.2 Local and Hybrid MSM Strategies

The proposed local negotiation strategy (**LMSM**) considers only the negotiation situation regarding each object alone, hence the name local. The **LMSM** strategy does not require the existence of common factors such as common issues. It interacts with the providers of each object in isolation and aims at reaching a high utility agreement.

The strategy decides the convexity of the concession curve for each group of delegates in each negotiation round taking into consideration the behaviors and the number of seller agents of a certain object without considering the behaviors or the number of seller agents for the other objects. The **LMSM** strategy depends on the number of the existing seller agents who behave favorably in terms of their concessions compared to their counterpart delegates' concessions. If the number of favorable agents is beyond a certain ϵ threshold, then the strategy chooses a tough negotiation stance or otherwise it chooses either a linear or a conceder stance. Algorithm 3 outlines the proposed mechanism. The algorithm iterates m times which is equivalent to the number of negotiation objects. In each iteration the data preparation process is first executed (lines *1-6*) then the conditional *if-statement* is used to count the number of existing seller agents who offered more concessions than their counterpart delegates' concessions in the previous negotiation round, see lines *7-24*.

Algorithm 3 LMSM algorithm

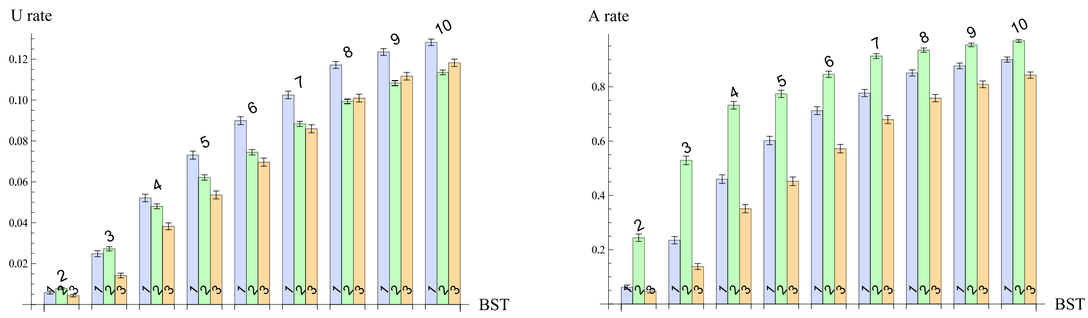
Require: $< X^{t-1}_{\mathbb{d}_{1,1}\leftrightarrow\mathbb{s}_{1,1}}[j], X^{t-1}_{\mathbb{d}_{1,2}\leftrightarrow\mathbb{s}_{1,2}}[j], ..., X^{t-1}_{\mathbb{d}_{1,n_1}\leftrightarrow\mathbb{s}_{1,n_1}}[j] >, ...,$
$< X^{t-1}_{\mathbb{d}_{m,1}\leftrightarrow\mathbb{s}_{m,1}}[j], X^{t-1}_{\mathbb{d}_{m,2}\leftrightarrow\mathbb{s}_{m,2}}[j], ..., X^{t-1}_{\mathbb{d}_{m,m_n}\leftrightarrow\mathbb{s}_{m,m_n}}[j] >$

1: **for** $i = 1 \rightarrow m$ **do**
2: $\quad \Delta\mathbb{d}_i =< \Delta\mathbb{d}_{i_1}, \Delta\mathbb{d}_{i_2}, ..., \Delta\mathbb{d}_{i_n} >$
3: $\quad \Delta\mathbb{s}_i =< \Delta\mathbb{s}_{i_1}, \Delta\mathbb{s}_{i_2}, ..., \Delta\mathbb{s}_{i_n} >$
4: $\quad \Delta F_i = \Delta\mathbb{s}_i - \Delta\mathbb{d}_i$
5: **end for**
6: $\Delta F = < \Delta F_1, \Delta F_2, ..., \Delta F_m >$
7: **for** $i = 1 \rightarrow m$ **do**
8: $\quad count = 0$
9: $\quad F_j^{(t_1,t_2)} i = select(t_1, t_2, \Delta F_i)$
10: $\quad$ **for** $k = 1 \rightarrow size(F_j^{(t_1,t_2)} i)$ **do**
11: $\qquad$ **if** $(F_j^{(t_1,t_2)}[i,k] > 0)$ **then**
12: $\qquad\quad count = count + 1$
13: $\qquad$ **end if**
14: $\quad$ **end for**
15: $\quad$ **if** $(count < \epsilon)$ **then**
16: $\qquad \beta = random(2, 5)$
17: $\quad$ **else if** $(count == \epsilon)$ **then**
18: $\qquad \beta = random(0.9, 1.1)$
19: $\quad$ **else**
20: $\qquad \beta = random(0.5, 0.89)$
21: $\quad$ **end if**
22: $\quad$ count = 0
23: $\quad add(V_{\beta^t}, \beta)$
24: **end for**
25: Return (V_{β^t})
26: **end algorithm**

To decide the value of β for a group of delegates in the next negotiation round, the decision making process is shown in lines *15-21*. If the number of favorable agents ($count$ in the algorithm, see line 8) is less than ϵ, then the buyer agent needs to take a lenient stance in order to not jeopardize reaching an agreement. In this case, the mechanism selects a β value randomly from a conceder space, i.e., $\beta \in [2, 5]$. When the number of favorable seller agents is equal to ϵ, then a linear behavior is selected, see line 18. Finally, when the number of favorable seller agents is greater than ϵ then the situation for the buyer agent allows for taking a tough negotiation stance which may guarantee an agreement with high utility, see line 20. The threshold value (ϵ) used in the experiments is 3.

5.3.2.1 Experimental Results and Discussion

To test the **LMSM** strategy, a few sets of experiments are designed and executed. The experimental settings are the same as in the previous section. The percentage of overlap between the agents' reservation intervals in the experiments of Figure 5.15 is 25%. Figure 5.15a shows that the **LMSM** strategy outperforms the *SR* strategy when the number of seller agents is 4 or more and performs similar to the *SR* strategy when the number of seller agents is 3 or less. If the utility rate is calculated per agreement rather than per negotiation instance, then the difference between the strategies **LMSM** and *SR* will be greatly noticeable in the favor of the **LMSMS** strategy.



(a) (b)

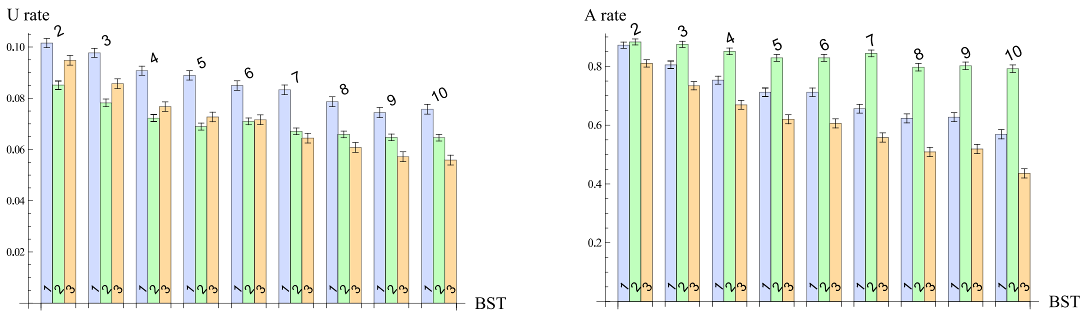
$(1 \rightarrow LMSM, 2 \rightarrow SR, 3 \rightarrow GS)$
(The numbers above the graph bars refer to the number of seller agents per objects)

Figure 5.15: *Testing the strategies LMSM, SR and GS; number of seller agents varies*

Since the agreement rate for the **LMSM** strategy is low when the number of seller agents is equal or less then 4 when compared to the agreement rate of the *SR* strategy, it is expected that its utility rate is negatively affected. However, for a large number of seller agents, the gap between the **LMSM** strategy and the *SR* strategy becomes small in terms of the agreement rate, see Figure 5.15b. The results regarding the agreement rate is normal since the **LMSM** strategy does not have the overall (global) view of the negotiation situation which makes it focus on reaching a valuable agreement over an object without considering the situations of other objects.

It is obvious that the *SR* strategy is effective in terms of scoring a high agreement rate when compared to *GS*. However, *GS* starts approaching the *SR* strategy in terms of the utility rate when the number of the seller agents is 7 and outperforms the *SR* strategy beyond that. The reason is that when the number of the seller agents increases, the gap between the agreement rates of the two strategies decreases which results in more utility rate for *GS*, see Figure 5.15a. Finally, Figure 5.15 shows that the **LMSM** strategy outperforms *GS* in both, utility rate and agreement rate, see Figures 5.15a and 5.15b.

Figure 5.16 shows the experimental results when the number of negotiation objects varies. The numbers shown above the *bars* of the figure indicate the number of negotiation objects. For each number of objects, the number of the seller agents is fixed and is equal to five. The only difference in the experimental settings here is that the number of negotiation objects varies. Figure 5.16 shows that the **LMSM** strategy outperforms the other two strategies in terms of utility rate across all numbers of negotiation objects. In addition, **LMSM** outperforms *GS* in terms of the agreement rate across all numbers of objects.

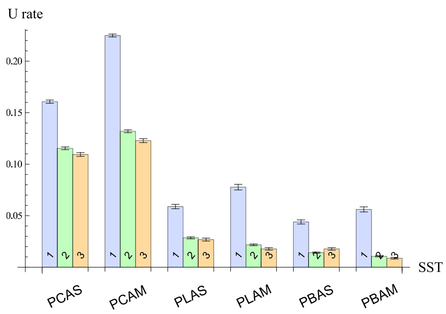


(a) (b)

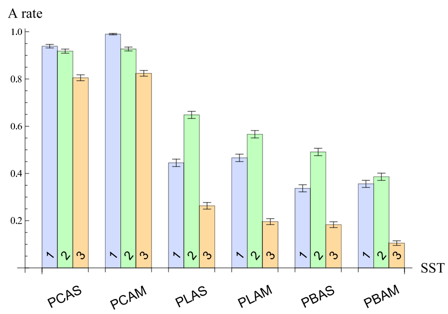
$(1 \rightarrow LMSM, 2 \rightarrow SR, 3 \rightarrow GS)$
(The numbers above the graph bars refer to the number of negotiation objects)

Figure 5.16: *Testing the strategies LMSM, SR and GS; number of objects varies*

The performance of the three strategies against seller agents who mix the time-dependent and the behavior-dependent tactics to generate their offers is shown in Figure 5.17. The number of seller agents in the experiment is 5. Figure 5.17a shows that the **LMSM** strategy outperforms the other two strategies significantly in terms of utility rate. When the seller agents are of *PCAS* or *PCAM* types, the **LMSM** strategy outperforms the *SR* in terms of agreement rate. When the seller agents are of types *PCAS* and *PCAM*, they tend to concede more which helps the **LMSM** to secure a high agreement rate. For all other seller types, the *SR* strategy records a better agreement rate. The **LMSM** outperforms *GS* in terms of utility rate and agreement rate in all cases. The *SR* strategy outperforms *GS* in terms of the agreement rate in all cases and performs equally or better than *GS* in terms of the utility rate except when the seller agents are of type *PBAS* in which case *GS* performs better than the *SR* strategy for the same reason explained in Section 5.3.1 in Figure 5.14a.



(a)

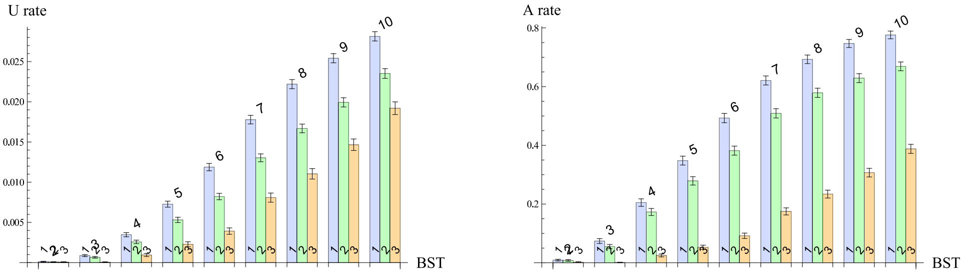


(b)

$(1 \rightarrow LMSM, 2 \rightarrow SR, 3 \rightarrow GS)$

Figure 5.17: *Testing the strategies GMSM, SR and GS; the seller agents mix between the time-dependent tactics and the behavior dependent tactic to generate their offers*

The hybrid MSM (**HMSM**) strategy is the combining of both, the **GMSM** and **LMSM** strategies. In addition to the deadline, the **HMSM** strategy needs two pieces of information to generate counteroffers. It needs the local reservation values for the negotiation issues and the convexity of the concession curves, i.e., β values. The **GMSM** mechanism (see Algorithm 2) provides the local reservation values while the **LMSM** provides the β values, see Algorithm 3. The empirical results show that the **HMSM** works best when the resource shifting is postponed until the buyer agent reaches an agreement(s). The reason is that, when the delegate agents of a certain object are in a difficult negotiation situation, the **GMSM** will probably shift some resources to help. In addition, the **LMSM** strategy will probably use a lenient negotiation stance with the providers of that object. It is obvious that the delegates in the difficult situation receive help from the two strategies while the delegate group that is in the better negotiation situation will be affected negatively in terms of reaching an agreement since the **GMSM** strategy reduces its resources and the **LMSM** strategy assigns it a Boulware β value.

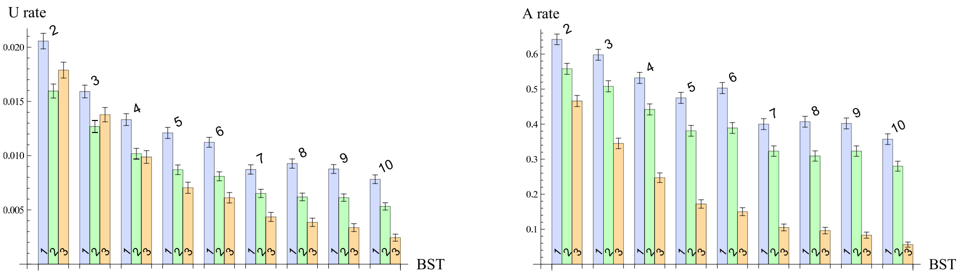


(a) (b)

$(1 \rightarrow HMSM, 2 \rightarrow SR, 3 \rightarrow GS)$
(The numbers above the graph bars refer to the number of seller agents per objects)

Figure 5.18: *Testing the strategies HMSM, SR and GS; number of seller agents varies*

The results shown in Figure 5.18 indicate that the **HMSM** strategy outperforms both the *SR* and *GR* strategies. The settings for the experiment used to generate the results shown in Figure 5.18 are: 10% or less overlap between the reservation intervals of the agents' negotiation issue. The amount of resource shifting during negotiation is 0 and the number of agents varies while the number of objects is 10. The results are interesting since the **HMSM** strategy shows good results in terms of both utility rate and agreement rate that outperform the other two strategies signficaltly and in all cases, see Figures 5.18a and 5.18b. When value γ used in Algorithm 2 is zero, then the **GMSM** is the same as the *SR* strategy in this case.



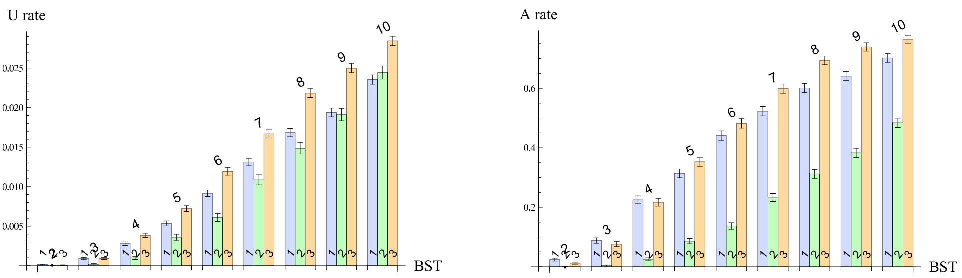
(a) (b)

$(1 \rightarrow HMSM, 2 \rightarrow SR, 3 \rightarrow GS)$
(The numbers above the graph bars refer to the number of negotiation objects)

Figure 5.19: *Testing HMSM, SR and GS; number of objects varies*

The settings of the experiment used to generate the results in Figure 5.19 are similar to the settings of the experiment used to generate the results in Figure 5.18. The difference is that the experiment used to generate the results in Figure 5.19 vary the number of objects while the number of seller agents used was 5. The results in Figure 5.19 show that the **HMSM** strategy outperforms the other two strategies significantly and in all cases, see Figures 5.19a and 5.19b.

The results shown in Figures 5.18 and 5.19 indicate that when the *global coordination* and the *local coordination* are combined, they produce better results than using either one alone. However, the **HMSM** strategy requires more computation since both the global coordination and local coordination mechanisms need to be executed.



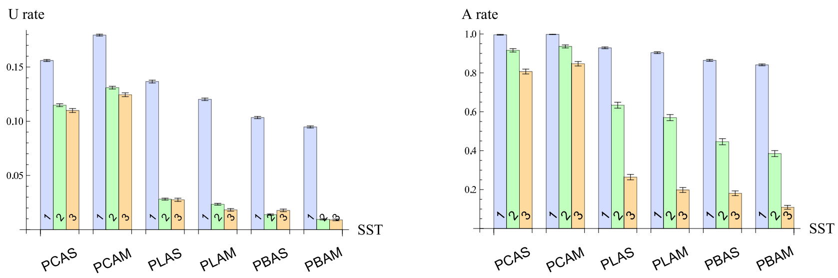
(a) (b)

$(1 \rightarrow GMSM, 2 \rightarrow LMSM, 3 \rightarrow HMSM)$
(The numbers above the graph bars refer to the number of seller agents per object)

Figure 5.20: *Testing GMSM, LMSM and HMSM; number of seller agents varies*

To confirm the conclusion that the **HMSM** performs better than the two proposed strategies, the **HMSM** strategy is tested against the strategies **GMSM** and **LMSM**. Figure 5.20 shows the experimental results. The hybrid strategy outperforms the global strategy and the local strategy in terms of utility rate and agreement rate. The other results are consistent since the **GMSM** strategy outperforms the **LMSM** strategy in terms of agreement rate while the **LMSM** strategy performs better than the **GMSM** strategy in terms of utility rate per agreement.

It is noticed that the difference between the **GMSM** and **LMSM** strategies in terms of agreement rate is high, see Figure 5.20b, while the difference between them in terms of utility rate is relatively small. The reason is that the **LMSM** achieves a higher utility rate per agreement while the **GMSM** achieves a lower utility rate per agreement. When the number of agents increases, see Figure 5.20a when the number of agents is 10, the **LMSM** strategy starts showing even a higher utility rate.



(a) (b)

$(1 \to HMSM, 2 \to SR, 3 \to GS)$

Figure 5.21: *Testing HMSM, SR and GS. The seller agents mix between the time-dependent tactics and the behavior dependent tactic to generate their offers*

The results of testing the hybrid strategy against the seller agents who mix between the time-dependent and behavior-dependent tactics are shown in Figure 5.21. Figure 5.21a shows that the **HMSM** outperforms the other two strategies in terms of utility rate. In addition, the hybrid strategies also outperforms the *SR* and *GS* strategies in terms of the agreement rate, see Figure 5.21b.

5.4 Summary

This section investigates the coordination scenarios **SMM** and **MSM** and presents coordination mechanisms that can be used in each scenario to coordinate the bidding strategy of a buyer agent during negotiation. Any object in any of these scenarios contains a single issue. Four novel coordination mechanisms are presented in this chapter. The first mechanism is designed to coordinate the bidding strategy for a buyer agent in the **SSM** scenario. The rest of the mechanisms targets the **MSM** scenario. In addition, the chapter shows an empirical analysis for different techniques that can be used to evaluate the behavior of a seller agent.

The coordination mechanism proposed for the **SSM** scenario depends on managing the convexity of the concession curves for the different buyer's delegates. The feedback from the seller agents in terms of their consecutive offers are used to control the slop of the delegates's in every negotiation round. The experimental results show that the proposed mechanisms outperforms (in most cases) the benchmark strategies in terms of the utility rates and performs similar in terms of the agreement rates. The main benchmark strategy relies on historical data to determine the value of the next proposal in every negotiation round.

Since the **MSM** scenario assumes multiple providers for each agent, two coordination levels are defined: global coordination and local coordination. The global coordination mechanism focuses on managing the local reservation values for the objects' issues. The global coordination mechanism changes the local reservation values by shifting resources from one group of delegates to another according to their need. The local coordination mechanism focuses on a given group of providers and manages the slop of the concession curve for each group of delegates accordingly. The hybrid mechanism combines both, the global and local coordination mechanisms. The experimental results show that the proposed global coordination strategy outperforms the global strategy proposed in the literature in terms of the agreement rates and performs similar or better in terms of the utility rates. The benchmark strategy reassigns new reservation values when a certain negotiation is ended. On the other hand, the proposed global strategy does not wait for a negotiation to finish before reassigning new reservation values, it rather assigns new reservation values based on the current need of delegates.

The experimental results show that the proposed global strategy performs better than the local strategy in terms of the agreement rates and vice versa in terms of the utility rates. On the other hand, the local strategy performs better than the other strategies in terms of the utility rates. It also outperforms the *GS* in terms of the agreement rates. The hybrid strategy outperforms other strategies in terms of the utility and agreement rates when the amount of resource shifting during negotiation is 0. However, the proposed strategies work best when the overlap percentages between the reservation intervals of issues are small. In other words, the proposed strategies work best under difficult negotiation environments. The same applies to the benchmark global coordination strategy. Moreover, the results show that the recent concession measure performs equal or better than the other measures when evaluating the behaviors of the opponents.

Most of the works in the literature address the single issue negotiation. This chapter proposes a coordination method that performs better than a state-of-the-art coordination method. In addition, the state-of-the-art coordination mechanism requires historical data while the proposed coordination method requires no historical data. Moreover, this chapter considers negotiations over multiple distinct objects while the work in the literature rarely considers concurrent negotiations over multiple distinct objects.

Chapter 6

A Single Object with Multiple Negotiation Issues

This chapter investigates the single object multiple issues and multiple providers (SMM) coordination scenario where a buyer agent negotiates with multiple seller agents over an object characterized by multiple issues. Firstly, a novel offer generation mechanism, the Iterative Offer Generation (IOG), is introduced. The mechanism is used by the buyer agent to generate counteroffers when it decides to use either a trade-off tactic or a concession tactic. Secondly, a novel one-to-many meta-strategy coordination mechanism is presented. The meta-strategy is based on the idea of alternating between a concession tactic and a trade-off tactic during negotiation when generating counteroffers. The decision to use either tactic depends on the level of cooperation by the seller agents in terms of their concession in the current negotiation. The experimental evaluation includes two parts: the meta-strategy evaluation part and the IOG-concession evaluation part. In addition to the agreement rate and the utility rate performance criteria, the social welfare and the fairness of the agreements criteria are also considered.

6.1 Introduction

In real life, people need to consider more than one issue during negotiation. In spite of the fact that the price is one of the most important issues in business negotiations, other issues such as reliability, delivery time and warranty time are also important. This chapter extends the previous chapter by considering a more realistic negotiation scenario where a negotiation object contains multiple issues. The **SMM** coordination scenario can represent a case in any of the motivating scenarios presented in Chapter 1. For example, a cloud client might want to negotiate with cloud providers over a service that has the issues price, size etc., see Section 1.2.1. In the supply chain domain, a customer can negotiate with multiple suppliers over price, quantity, delivery time and the quality of some raw material, see Section 1.2.3. Finally, a travel agent can negotiate price and travel time of a certain journey.

When two agents negotiate over multiple issues, they can follow the sequential procedure, the simultaneous procedure or the package deal procedure. The sequential procedure allows agents to negotiate issues in sequence, i.e., one after another. In the simultaneous procedure, agents negotiate the issues simultaneously but independently of each other. When agents use the package procedure, each agent proposes a value for each issue (concurrently) in each negotiation round. The package deal is proven to be the optimal procedure for each party [40]. Since we are dealing with concurrent one-to-many negotiation, we assume that a buyer agent proposes a value(s) for each issue of each object in the same time frame and receives offers from all seller agents in the next time frame.

This chapter investigates the **SMM** coordination scenario where a buyer agent is negotiating with multiple seller agents over an object characterized by multiple negotiation issues, see Figure 6.1. Many possible application domains can be represented by this form of negotiation, such as the supply chain domain, the task allocation and order fulfillment problems [157]. For example, a manufacturer needs to procure raw materials and in most cases, more than one supplier exists in the market. One of the possible approaches for procuring raw materials is to negotiate with multiple potential suppliers concurrently. In the service oriented domain for example, a client can negotiate with multiple service providers concurrently over the SLAs for the purpose of procuring one service or more [100].

The coordination approaches presented in the previous chapter were based either on managing the convexity curve or managing the local reservation values during negotiation. Since this chapter assumes multiple negotiation issues per object, the proposed

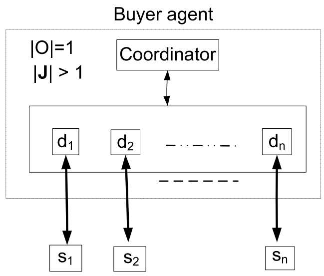


Figure 6.1: *One object with multiple negotiation issues*

coordination mechanism is a meta-strategy that is based on alternating between trade-off and concession negotiation tactics during negotiation. The main difference between the concession tactics and the trade-off tactics is that a trade-off tactic generates different counteroffers on the buyer's current iso-curve (indifference curve) that have the same utility value, see Section 2.3.3.5. The buyer agent can stay on the same indifference curve for several negotiation rounds which means that the buyer agent generates different counteroffers that have the same utility of the indifference curve. On the other hand, the concession mechanism generates counteroffers with lower utility values (i.e., provide more value to the opponents) in each negotiation round.

The trade-off is used when the buyer agent faces a favorable negotiation situation where it keeps its current aspiration level (current utility value) unchanged and at the same time attempts to generate counteroffers with better values for its opponents. On the other hand, the concession strategy is used when the buyer agent faces unfavorable negotiation situation and there is a risk of not reaching an agreement if it does not concede. The main coordination problem in this approach is to answer the question about when the buyer agent should leave its current iso-curve and move to another lower utility iso-curve. In addition, the appropriate distance between the old iso-curve and the new iso-curve is another problem. Moreover, if the buyer agent decides to use a concession strategy, what would be the negotiation stance, i.e., Boulware, linear or conceder? The proposed coordination approach in this chapter propose some answers to these questions.

The proposed meta-strategy is not only competitive, but also cooperative. It is competitive in the sense that it strives to achieve the best possible agreement for the buyer agent and cooperative in the sense that it attempts to generate counteroffers that provide better values to the opponents. A trade-off tactic assumes that the agents have *divergent preferences* over issues. If the negotiating agents have convergent preferences over the negotiation issues, then the negotiation game becomes a *zero-sum* game and the room for using the trade-off does not exist, see Section 2.3.3.5.

This work adapts the work in [34] [121] by considering a more complex situation where one agent is negotiating with multiple agents concurrently. The work in [34] [121] considers mainly a meta-strategy for bilateral negotiation where the decision making process involves only two agents. In the next section, the proposed *iterative offer generation* tactic introduced. The meta-strategy is introduced in Section 6.3.

6.2 Iterative Offer Generation Tactics

The iterative offer generation (**IOG**) tactic is a cooperative and competitive mechanism for generating offers. The **IOG** strategy is designed to work in two cases. Firstly, when an agent decides to use the trade-off technique to propose offers. Secondly, when the agent decides to propose an offer using a concession strategy. First, the *IOG-trade-off* is introduced, then the *IOG-concession* tactic is presented.

–IOG-trade-off:

When an agent decides to use the trade-off mechanism, the agent ranks the issues under negotiation according to their importance from the opponent's point of view. Second, it concedes on the most important issue - the *current most important issue (CMII)* - from the opponent's point of view using, for example, a time-dependent tactic with a conceding mode, i.e., $\beta > 1$. While keeping the values of other issues from the last agent's offer unchanged, Equations 3.2 and 3.3 (see Section 3.2) are used to calculate a value for the least important issue - the *current least important issue (CLII)* - from the opponent's point of view that would keep the agent on its current iso-curve, i.e., $U^{\mathbb{d}}(x^{t+1}_{\mathbb{d}\to\mathbb{s}}[J_q]) = U^{\mathbb{d}}(x^{t}_{\mathbb{d}\to\mathbb{s}}[J_q])$. If the value reaches beyond the reservation limit of the *CLII*, then the value of the *CLII* becomes its reservation limit and the agent needs to update the second least important issue which becomes the *CLII* using Equations 3.2 and 3.3 . The process is repeated until the agent finds an offer with a utility equal to the utility of its current iso-curve. Each iteration of the **IOG-trade-off** mechanism involves modifying either one or two values: the *CMII* and/or the *CLII*. Figure 6.2 shows an illustration to the **IOG-trade-off** technique. The figure shows eight negotiation issues ordered from the most important issue to the opponent in the far left to the least important issue to opponent in far right. It also shows the reservation value of each issue. The utility of the last offer is 0.6 which is the utility of the current iso-curve, see figure 6.2. In the first iteration, the agent concedes on issue j_1 which is the most important issue from the opponent's point of view by changing its value from 40 to 50. This amount of concession changes the utility of the composite offer from 0.6 to 0.5. In this case, the agent needs to modify the values of some other issue(s) to bring the utility to 0.6. As the technique specifies, it uses Equations 3.2 and 3.3 to calculate a new value for issue j_8. Assume that the calculated value is 0 that is required to change the utility of the offer from 0.5 to 0.6, see *iteration 2*. The problem here is that the minimum value that can be assigned to issue j_8 is 10. The issue j_8 is assigned 10 and the calculated utility become 0.55, see *iteration 3*. The next step is to move to the second least important issue (j_7) and modifies its value. Assume that Equations 3.2 and 3.3 assign the value 43 to j_7 that makes the utility of the offer equals to 0.6. At this point, the algorithm stops. In case changing the value of issue j_7 does not bring the utility to 0.6, then the algorithm moves to issue j_6 etc. Finally, if it is not possible to concede on issue j_1 because the last value of the issue j_1 was its reservation value, then the algorithm concedes on the second most important issue from the opponent's point of view which is j_2 in our example.

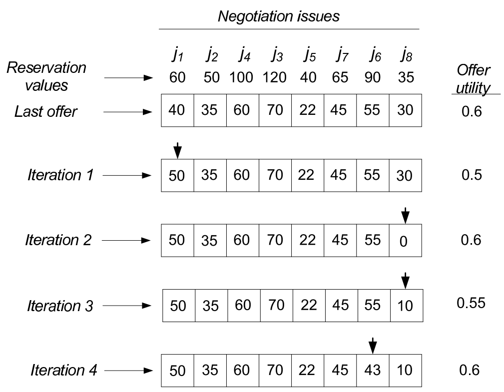


Figure 6.2: *Illustration of the IOG-trade-off mechanism*

It is assumed that an agent is capable of ranking the issues from its point of view, for example, an agent is able to say whether money or delivery time is more important. However, ranking the same issues from the opponent's point of view is a nontrivial task and it is an important research matter, e.g., see [22]. The opponent's issue ranking mechanism proposed here works as follows: An agent finds the percentage of the concession offered on each issue in the previously received two offers, then it ranks the importance of the issues accordingly. For example, Table 6.1 shows offers exchanged between two agents in two negotiation rounds for the price and quantity issues. The percentage of the seller concession on the price is $(100 - 10)/100 = 10$ % while the percentage of its concession on the quantity is $(11 - 5)/11 = 54.54$ %. It can be detected that the price issue is more important to the seller agent than the quantity issue, hence the buyer agent can rank the issues according to their importance from the seller agent's point of view: $\{price \succ quantity\}$.

Table 6.1: *Example of exchanged offers over two negotiation issues*

		Price	Quantity
round 1	seller	100	5
	buyer	10	50
round 2	seller	90	11
	buyer	30	48

An agent using the explained ranking method repeats the ranking process at the start of each negotiation round since the assumption is that the opponent may change its mental state and hence the importance of different issues may change during negotiation. This ranking method is flexible since an agent can detect changes in its opponent's mental state by tracking the percentages of concessions offered on each issue in each negotiation round. However, in many cases, an agent would have some experience or domain knowledge that enables it from guessing the rank of negotiation issues from its opponent's point of view especially when the negotiating agents are of buyer and seller types. As the issue ranking is not in the scope of this thesis, in the experimental work, a buyer agent is assumed to have partial knowledge about the importance of the issues from the sellers' point of view.

As previously stated, one of the two important conditions that are necessary to apply the trade-off mechanism effectively is that agents have divergent preferences over at least one issue (see Section 2.3.3.5). It is obvious from Table 6.1 that the seller agent is more sensitive towards the price when compared to the buyer agent, while the buyer agent is more sensitive to the quantity when compared to the seller agent. In this case, both agents have divergent preferences over the two issues and the buyer agent concedes more on the price (while staying on its indifference curve) while the seller agent concedes more on the quantity issue while staying on its current indifference curve assuming that both agents use the **IOG-trade-off** mechanism.

A second numerical example that represents a seller agent ($\forall j_i \in \mathbf{J}, IV_{j_i} > RV_{j_i}$) uses Equations 3.2 and 3.3 to find the next offer is given next. Assume $\mathbf{J} = \{j_1, j_2, j_3\}$ and the reservation intervals for the issues are $j_1 \in [10, 30], j_2 \in [20, 40], j_3 \in [15, 35]$. Assume that the issues are ranked as follows:$\{j_2 \succ j_1 \succ j_3\}$ and the last proposed composite offer was $\{j_1 = 20, j_2 = 30, j_3 = 25\}$. Let the utility of the current indifference curve be equal to 0.6 and the weight vector $\mathcal{W} = \{0.5, 0.3, 0.2\}$. According to the **IOG-trade-off**, an agent concedes first on the most important issue which is j_2. Assume that the agent decides to offer 22 on the issue j_2 using a time-dependent tactic with a conceder mode. Now, the value of j_1 is kept as is for the current iteration and the objective is to find a value for the issue j_3 using the equations 3.2 and 3.3 as follows. First, the u_{j_3} needs to be found from equation 3.3 where $0.6 = 0.5*((30-20)/(30-10))+0.3*((40-22)/(40-20))+0.2*u_{j_3}$. Solving the equation results in $u_{j_3} = 0.4$. The next step is the find the value of j_3 that produces the utility 0.4 from equation 3.2 as follows: $0.4 = (35-x_{j_3})/(35-15)$, solving for x_{j_3}, $x_{j_3} = 27$ which means that the next composite offer will be $\{j_1 = 20, j_2 = 22, j_3 = 27\}$.

The above example required only one step since the value of the issue j_3 that is needed to keep the current indifference curve utility (i.e., 0.6) did not go beyond the reservation value of the issue j_3. If the required value of the issue j_3 to keep the current utility level is, e.g., 37, then the value of the issue j_3 is assigned 35 which is its reservation value and the next iteration of the algorithm proceeds to find a new value for the issue j_1 (the current least important issue) that keeps the current utility unchanged. If this step is also unsuccessful, then the value $j_2 = 22$ needs to be changed, i.e., a higher value needs to be proposed to keep the current utility of the indifference curve.

–IOG-concession:

The **IOG-concession** is a concession offer generation method where an agent needs first to decide its current acceptable utility value that is less than its previous one. The next step is to find a value for each issue in the composite offer to be proposed next. The agent starts conceding on the *CMII* from the opponent's point of view. The process here is similar to the process of computing the value of a composite offer in case the agent uses the **IOG-trade-off** mechanism. The difference here is that the utility of the current composite offer is lower than the utility of the previous composite offer.

It is true that an agent cares about the weighted average utility (when negotiation issues are linearly dependent) which means that the agent may concede on any issue that brings its utility to the designated utility level and the issues can be selected randomly since the utility of the composite offer is the important criterion here. However, adopting the **IOG-concession** mechanism has two benefits:

- In case agents have divergent preferences over issues, the **IOG-concession** mechanism can result in a better offer value for the opponent which may improve the chance of reaching an agreement quickly. In addition to saving time by reaching an agreement quickly, if an agreement is reached in the current negotiation round, the conceding agent does not lose more utility if negotiation continues. It can happen that the conceding agent may need to concede again in the next negotiation round.
- The **IOG-concession** mechanism may improve social welfare when the proposing agent provides more concessions on the issues that are more important for the opponents first.

One way to determine the required aspiration level at any time during negotiation is to use Equation 6.1 that depends on both, the time elapsed and the β value. If an agent is in desperate need for an agreement, it uses large β values which means that the agent is willing to accept low utility offers in exchange for reaching an agreement. The value of β can cause a conceder, a Boulware or a linear behavior which is similar to the role of β in the time-dependent tactics.

$$U^{\mathbb{d}}(x^t_{\mathbb{d}\to\mathbb{s}}[J_q]) = 1 - (t/t^{\mathbb{d}}_{max})^{(1/\beta)} \tag{6.1}$$

In Equation 6.1, t is the current time, $t^{\mathbb{d}}_{max}$ is the agent's deadline. For example, at time $t = 0$, the results of the equation $(t/t^{\mathbb{d}}_{max})^{(1/\beta)}$ equals 0, then the required aspiration level equals 1. That is normal since an agent at the start of negotiation starts with high aspiration level, then it concedes by reducing its aspiration level during negotiation.

In one-to-many negotiations, other factors can be used to determine the current required utility value such as the number of negotiation instances. More negotiation instances means more opponents and hence better bargaining power for the agent on the '*one*' side. In other cases, an agent chooses a fixed amount of concession in each negotiation round. For example, an agent may concede 0.05 in each time it decides to use a concession offering mechanism.

6.3 The Meta-Strategy Model

The proposed negotiation meta-strategy is a strategy that selects a certain offer generation technique from a predefined set of offer generation techniques during negotiation. The selection criteria depends on the current negotiation situation in terms of the number and the behaviors of the current opponents. As mentioned in the solution approach, see Section 4.3, the buyer agent may change its negotiation strategy by changing any of its strategy components or their associated parameters. This chapter considers the Θ strategy component which is the set of offer generation techniques and their associated parameters. In particular, the proposed meta-strategy may use a different offer generation mechanism in each negotiation round.

As mentioned in the introduction of this chapter, the buyer agent alternates between a concession tactic and a trade-off tactic during negotiation. The buyer agent uses the trade-off tactic whenever the situation is favorable, otherwise the buyer uses a concession tactic. Deciding whether the buyer agent is in a favorable situation depends on both, the number of opponents and their behaviors in terms of their concessions. If the opponents are offering generous concessions then the situation is favorable for the buyer agent, otherwise it is not. More opponents means the buyer agent has more bargaining power and hence the situation is favorable.

Algorithm 4 summarizes the meta **SMM** strategy (**MSMM**). The data preparation steps are similar to the data preparation presented in Chapter 4. The data preparation is shown in lines $1-7$.

When considering the situation where the buyer agent has the privilege to renege from a temporary agreement without paying a penalty, the approach works as follows: in the first few negotiation rounds, the buyer agent classifies the seller agents into two groups, a *favorable group* and *unfavorable group* depending on their relative behavior (relative to the buyer's behavior) by comparing the amount of concessions offered by each delegate d_i and its opponent s_i. The buyer agent uses the meta-strategy with the favorable group, while using the concession strategy with the unfavorable group.

At this point, we have a few problems to deal with. The first one is how an opponent's behavior is measured? The second one is how much the buyer agent concedes when it chooses to use the concession strategy? A third one is how the distance between two indifference curves is determined when the buyer agent moves from one indifference curve to another during negotiation where the distance is measured in terms of utility.

Algorithm 4 (MMSM)

Require: $< X^{t-1}_{\mathbb{d}_{1,1}\leftrightarrow\mathbb{s}_{1,1}}[j], X^{t-1}_{\mathbb{d}_{1,2}\leftrightarrow\mathbb{s}_{1,2}}[j], ..., X^{t-1}_{\mathbb{d}_{1,n_1}\leftrightarrow\mathbb{s}_{1,n_1}}[j] >, ...,$
$< X^{t-1}_{\mathbb{d}_{m,1}\leftrightarrow\mathbb{s}_{m,1}}[j], X^{t-1}_{\mathbb{d}_{m,2}\leftrightarrow\mathbb{s}_{m,2}}[j], ..., X^{t-1}_{\mathbb{d}_{m,m_n}\leftrightarrow\mathbb{s}_{m,m_n}}[j] >$

for $i = 1 \rightarrow n$ **do** ▷ see Section 4.3, n is the number of seller agents
  $F_i = U\mathbb{s}_i - U\mathbb{d}_i$
end for
$\Delta F = < F_1, F_2, ..., F_n >$
for all ($F_i \in \Delta F$) **do**
  if ($F_i > 0$) **then**
    $add(fs, \mathbb{s}_i)$
  else
    $add(fs^{'}, \mathbb{s}_i)$
  end if
end for
if ($fs \neq \emptyset$) **then**
  NegoTatcic = trade-off
end if
if ($fs^{'} \neq \emptyset$) **then**
  NegoTatcic = time-dependent
end if
if ($fs \neq \emptyset$ and $fs^{'} == \emptyset$) **then**
  $set = sort(fs)$
  $fs^{'} = take(set, 1, |set|/2)$ ▷ integer division
  $fs = take(set, |set|/2 + 1, |set|)$
end if
if ($fs == \emptyset$ and $fs^{'} \neq \emptyset$) **then**
  $set = sort(fs)$
  $fs^{'} = take(set, 1, |set|/2)$ ▷ integer division
  $fs = take(set, |set|/2 + 1, |set|)$
end if
end algorithm

In this chapter, the *utility difference* between consecutive offers is considered instead of considering the difference in concessions for the purpose of evaluating the opponents. The reason is that the negotiation object is characterized by several issues and it is difficult to consider the difference in concession between each pair of issues since evaluating the behavior of an opponent becomes more difficult given that agents may have different priorities over the negotiation issues. The utility difference evaluates the opponent agents and works equally as well as the concession difference. The process of using the utility difference is shown in lines 1-3 in Algorithm 4. In the algorithm, $U\mathbb{s}_i$ stands for the difference in utility between the last two offers proposed by the seller agent $\mathbb{s}_i$ whereas $U\mathbb{d}_i$ stands for the difference between the last two counteroffers proposed by the delegate $\mathbb{d}_i$. Lines *5-11* classify the current seller agents into either a favorable set (fs) or unfavorable set ($fs^{'}$) depending on the results in the utility difference shown in lines *1-3*. If the difference in utility between the last two counteroffers of a delegate $\mathbb{d}_i$ is more than the difference in utility between the two offers of seller agent $\mathbb{s}_i$ (F_i in Algorithm 4) then the seller agent $\mathbb{s}_i$ is added to the favorable group fs, otherwise it is added to the unfavorable group $fs^{'}$. The classification process is performed at the start of negotiation. The buyer agent chooses to use a trade-off tactic with the fs group and a concession tactic with the $fs^{'}$ group.

It can happen that all the seller agents are classified in the set fs. In this case, if the buyer agent chooses to use a trade-off tactic, it might jeopardize reaching an agreement. To reduce the risk of not reaching an agreement, lines *18-20 sort* the fs set ascendingly and take the first half of the seller agents and assign it to a new $fs^{'}$ set and assign the second half (the more favorable seller agents) to a new fs set. The algorithm uses the meta-strategy with the new fs set and the concession strategy with the new $fs^{'}$ set. If all seller agents are assigned to the $fs^{'}$ set, then a similar procedure is applied to ensure that the buyer agent does not use only a concession tactic with all seller agents, see lines *23-26*.

When the buyer agent uses a trade-off negotiation tactic, it needs to decide when to move from one iso-curve to another during negotiation, since if it stays on the same iso-curve for a long time, it might jeopardize reaching an agreement. The reason is that the buyer agent could reach a point where it is difficult to propose new counteroffers to the seller agents that have extra value for them. It means that the buyer agent is not willing to concede anymore from the sellers' point of view which might end the negotiation with a conflict outcome. On the other hand, since agents are negotiating under incomplete knowledge, the buyer agent cannot tell when its current proposal does not provide any added value to its opponent than the previous one. However, since the buyer agent is negotiating with multiple seller agents, it can use the behaviors of the seller agents with whom it uses the trade-off tactic to decide when to move from one iso-curve to another. Deciding when to move from the current iso-curve to a new iso-curve with lower utility is considered next.

The buyer agent needs to define a deadlock point where it should move to a new iso-curve in the next negotiation round. There could be many signs for a deadlock point. For example, if the seller agents start offering proposals with lower utility than the previous ones, then this could be a sign for a deadlock. Since the seller agents in this thesis are assumed to offer equal or more utility proposal values than the previously offered ones, a different deadlock indicator needs to be considered. As a proposed solution, the buyer agent finds the first-order utility difference (S_u) from the last received two offers by each member in the set fs and the first-order utility difference (B_u) from the last two counteroffers proposed by their counterpart delegates. The buyer agent subtracts B_u from S_u, i.e., $u_{diff} = S_u - B_u$. If the maximum number in the set u_{diff} is less than or equal to 0, then the buyer agent reaches a deadlock point and needs to move to a new iso-curve. It means that none of the seller agents in the set fs offers more concession than the concession offered by its counterpart delegate in the last two negotiation rounds which is considered unfavorable situation for the buyer agent.

When the buyer agent using the **MSMM** strategy decides to move to a new iso-curve at time t, the distance between the old iso-curve and the new iso-curve is based on the smallest first-order difference in the utility offered by any seller agent in fs in the last two negotiation rounds. In other words, the buyer agent reduces its aspiration level by the amount of the least utility difference offered by any seller agent in fs. The intuition behind this decision is to imitate the concession of the most difficult opponent in fs that improves the chance of reaching a valuable agreement for the buyer agent. Other work in the literature [36] assumes a fixed distance between iso-curves. However, this is a strong assumption since other factors need to be considered such as time, behaviors of the opponents, etc.

6.4 Experimental Evaluation

This section shows the experimental results for testing both, the **MSMM** strategy and the **IOG-concession** tactic. All the results are analyzed and discussed.

6.4.1 Experimental Settings

The buyer agent uses the time dependent-tactic to generate its first two counteroffers then it uses either the **MSMM** strategy or the **IOG-concession** tactic to generate the rest of the counteroffers. The **MSMM** strategy is tested against two buyer agents who use different negotiation strategies to generate their counteroffers. Since the results presented in Chapter 5 show that the *eCN* strategy proposed in [106] outperforms most of the strategies in the literature, it is selected as a benchmark strategy. In addition, as a base benchmark strategy, the general negotiation strategy (*GS*) is also used. The *GS* is a strategy where the buyer agent does not change any of its negotiation variables during negotiation and it can be either a patient strategy or a desperate strategy. As explained in Chapter 5, the desperate strategy accepts the first acceptable agreement and quits negotiation while the patient strategy keeps negotiating until it reaches its deadline or all the seller agents quit negotiation. The general strategy used in this section uses the patient technique since all the buyer agents are assumed to keep negotiating with their opponents until they reach their deadlines or all the opponents quit negotiation. When one of the these two conditions hold, each buyer agent selects agreement with the highest utility. Since the **IOG-concession** tactic is a concession tactic, it is tested against *GS* which is considered a concession tactic too.

In all the experiments of this chapter, when an agent decides to accept an offer, it first checks for the utility of the received offer, if it is equal to its current aspiration level or more, then the agent checks whether each value of each issue in the received offer is more/less than its reservation value. If the answer is yes, then the offer is accepted, otherwise the offer is rejected. Moreover, the experiments used to generate the results in this chapter assume that the buyer agents and the seller agents have divergent preferences over the negotiation issues.

The following points highlights the general experimental settings:

- **Deadlines.** If the system does not require a fixed negotiation time for all agents, a deadline is randomly selected from the interval $[5, 30]$ at the start of each negotiation instance for all seller agents. To study the performance of different negotiation strategies under different deadlines. Experiments are designed to test the performance of the different buyer strategies when the buyer agents have both, shorter and longer deadlines than the seller agents' deadlines. In all experiments, the buyer agents have the same deadline that is selected randomly from a chosen interval. In addition, the buyer strategies are also tested when all agents (buyers and sellers) have equal deadlines.

- **Agent types.** An agent can be either time-dependent, behavior-dependent or mixed type. The mixed type agent means that the agent mixes between the time-dependent and the behavior-dependent tactics when generating its offers. Since the benchmark *eCN* agent relies only on changing the convexity curve during negotiation to generate its counteroffers, both *eCN* and *GS* buyer agents use the time-dependent tactics to generate their counteroffers. At the start of each negotiation instance, all buyer agents are assigned the same β value selected randomly from the interval $[0.1, 5]$. At the start of each negotiation instance, each seller agent selects a β value randomly from the same interval. In addition, an experiment is designed to test the buyer strategies when the seller agents use a mixed offer generation strategy.

- **Length of the agreement zone**. The performance of different strategies are tested for different lengths of agreement zones, i.e., different percentages of overlaps between the reservation intervals of negotiation issues of buyer agents and seller agents, see Section 4.5.2.

- **Number of agents and number of issues.** The proposed **MSMM** and **IOG-concession** strategies is tested with different number of seller agents and with different number of negotiation issues per object. To test how different buyer strategies are affected by the different number of seller agents, the experiment starts with 2 seller agents then $3, 4, ..., 10$ agents. While the number of seller agents are changed, the number of issues is fixed. On the other hand, to test the strategies against different number of issues, the experiment again starts with 2 issues then $3, 4, ..., 10$ issues per object. While changing the number of issues, the number of seller agents is fixed.

6.4.2 Experimental Results and Discussion

This section shows the results of the experiments and discusses the results. First, the performance of the **MSMM** strategy is tested when the buyers' deadline is smaller, larger or equal to the seller agents' deadlines. Second, the strategy is also tested when the length of agreement zones between the buyer agents and the seller agents are small and large. In addition, the **MSMM** strategy is tested against seller agents who mix between the time-dependent tactics and the behavior-dependent tactics to generate their offers. On the other hand, the **IOG-concession** tactic is tested when all agents select random deadlines from the same interval and when all agents have equal deadlines.

In the experiments, four evaluation criteria are considered: *utility rate, agreement rate, Nash product rate and utility difference rate*. Nash product rate is used as a performance criterion for the social welfare [104]. Large Nash product rate indicates better social welfare. The utility difference rate is the absolute difference between the agreement utility of a seller agent and its counterpart delegate. The utility difference rate indicates the fairness of the agreements, the lowest utility difference rate the better.

As a reminder of the notation used in the figures of this section, the *BST* label of the *x-axis* stands for the buyer strategies. Each *y-axis* label refers to a different performance criteria: *U rate* is the utility rate, *A rate* is the agreement rate. *Nash prod.* is the Nash product and the *U diff.* stands for the utility difference. The utility rates, the Nash product rates and the utility difference rates shown in the figures of this chapter are calculated per number of the agreements achieved.

In all the experimental results shown in this chapter, when the number of agents per object varies, the number of issues per object is set to 5 and when the number of issues per object varies, the number of seller agents per object is set to 5 too. For each different number of seller agents per object or different number of issues per object, the experiment is repeated 1000 negotiation rounds. The results are averaged and plotted.

6.4.2.1 Testing under Different Deadline Lengths

The specific experimental settings for testing the **MSMM** strategy when the buyer agents have shorter deadlines, longer deadlines and equal deadlines to the seller agents' deadlines are presented in Table 6.2.

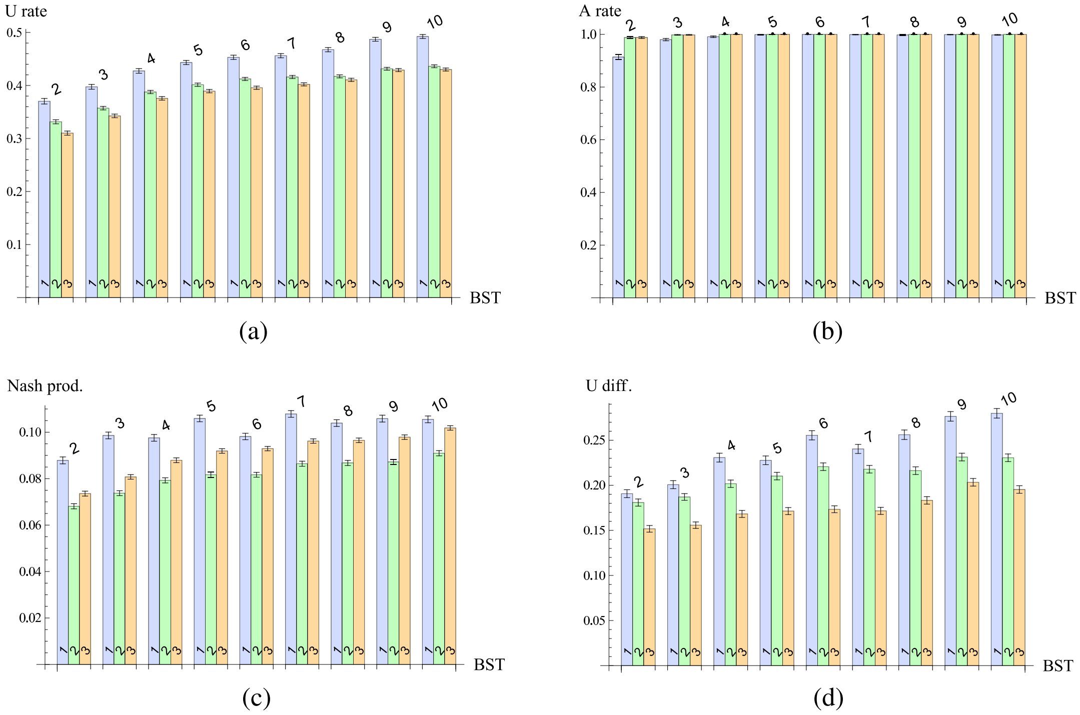
Table 6.2: *Experimental settings of different deadline lengths*

Agents or issues per object	Deadline description	Buyers' deadlines	sellers' deadlines	Buyers' beta value	sellers' beta values	Overlap	Figure name
Number of agents varies	Buyers have shorter deadlines	[5-30]	[31-50]	[0.5-5]	[0.5-10]	[0%-100%]	6.3,6.4
Number of issues varies	Buyers have shorter deadlines	[5-30]	[31-50]	[0.5-5]	[0.5-10]	[0%-100%]	6.5
Number of agents varies	Buyers have longer deadlines	[31-50]	[5-30]	[0.5-5]	[0.5-10]	[0%-100%]	6.6
Number of issues varies	Buyers have longer deadlines	[31-50]	[5-30]	[0.5-5]	[0.5-10]	[0%-100%]	6.7
Number of agents varies	All agents have equal deadlines	-	-	[0.5-5]	[0.5-10]	[0%-100%]	6.8
Number of issues varies	All agents have equal deadlines	-	-	[0.5-5]	[0.5-10]	[0%-100%]	6.9

The overlap in Table 6.2 refers to overlap between the reservation intervals of the negotiation issues. The columns in Table 6.2 starting from "Buyer's deadlines" to "Overlap" show intervals where a random number from each interval is selected randomly to specify a certain negotiation parameter for each agent at the start of every negotiation round. All buyer agents are assigned the same deadline and the same β value at the start of every negotiation round. Random overlap percentages are selected from the interval $[0\% - 100\%]$ for each issue where the seller agents can have different overlap percentages for the same issue. In addition, a deadline value and a β value are selected randomly from the intervals shown in Table 6.2 for each seller agent at the start of every negotiation round. For example in a certain negotiation round, seller agent 1 can have 20 as a deadline value while seller agent 2 can have 25 as a deadline value etc. The same applies for the other parameter values. This is to ensure that the seller are different while the buyer agents are the same except for the bidding strategy they use.

The experimental results when the buyer agents have shorter deadlines than their opponents' deadlines are shown in Figure 6.3. When the buyer agents have shorter deadline lengths, they reach their reservation values before the seller agents do and the same applies for the seller agents.

The results in Figure 6.3 show that the **MSMM** strategy outperforms the *eCN* and *GS* strategies in terms of *utility rates*, see Figure 6.3a. The three buyer agents have no problem in terms of the agreement rate as shown in Figure 6.3b except that the **MSMM** strategy has lower agreement rates than the other two strategies when the number of seller agents is small ≤ 3. Consider the number of seller agents per object is small, e.g., 2, the classification process in the **MSMM** strategy then assigns one seller agent to fs



$(1 \rightarrow MSMM, 2 \rightarrow eCN, 3 \rightarrow GS)$

(*The numbers above the graph bars refer to the number of seller agents per object)*

Figure 6.3: *The buyer agents have shorter deadlines than the seller agents' deadlines and the number of seller agents per object varies.*

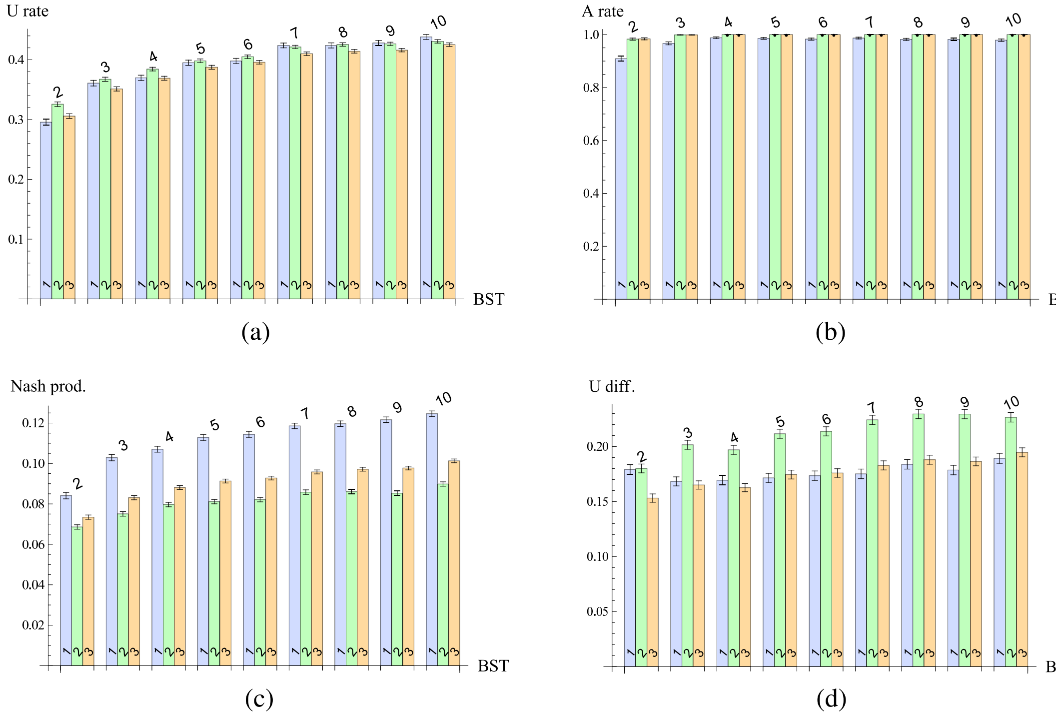
and another to fs'. The classification process may change the positions of the seller agents in the next negotiation round and since the buyer agent has lower deadline than its opponents' deadlines, it may have not enough time to adapt to the situation after the new classification and consequently miss the agreement. The reason behind the fact that the buyer agents do not have a problem in reaching near 100% agreement rate in the given settings is that the buyer agents offer their reservation values before the seller agents do. In addition, there are multiple providers and the chance of reaching an agreement with at least one of them is high given the fact that agreement zones between the buyer agents and the seller agents do exist.

The *Nash product rates* of the **MSMM** strategy is higher than the Nash product rates of the other benchmark strategies, see Figure 6.3c. Because the **MSMM** strategy is both competitive and cooperative, see Section 6.2. When the number of seller agents per object increases, the Nash product rate increases for all strategies. The reason is that the buyer agents achieve higher utility per agreement when the number of the sellers is high which increases the Nash product rates. The *eCN* strategy has the lowest Nash product rates since it is a very competitive strategy and does not cooperate with its opponents. The Nash product rates for *GS* is always higher than the Nash product rates of the *eCN* strategy because *GS* offers more proposal values to its opponents which increases the Nash product agreement value. When the number of seller agents per object is high enough (> 10), *GS* approaches the **MSMM** in terms if Nash product rates, see Figure 6.3c. The reason is that when the number of the sellers increases, the buyer agent using *GS* has the opportunity to select a more valuable agreement. In addition, *GS* offers proposals that have better utility values to its opponents in every negotiation round. This results in improved Nash product rates.

The *utility difference* is shown in Figure 6.3d. The utility difference indicates the fairness of an agreement. If the utility difference between two agreement utilities is 0, it means that each opponent achieves the same utility from the agreement. If the utility difference for a strategy is lower than the utility difference for another, then the first strategy achieves an agreement that is more fair than the agreement archived by the second strategy. In all cases shown in Figure 6.3d, *GS* has lower utility difference rates than the other two strategies. The utility difference rates of the **MSMM** strategy is higher than the utility difference rates of the *eCN* and *GS* strategies. Figure 6.3d shows that the difference in utility difference between the *eCN* strategy and **MSMM** strategies is relatively small when the number of seller agents per object is small. When the number of seller agents becomes large, the **MSMM** strategy becomes more competitive and secures high utility agreement when compared to the utility agreement of its opponent.

The *GS* achieves the best results in terms of utility difference because *GS* is a concession strategy that keeps offering concessions throughout negotiation until it reaches an agreement. In addition, the seller agents in this experimental settings use a concession strategy which makes them keep offering concessions throughout negotiation too. Therefore, the buyer agent using *GS* and the seller agents using their own concession strategy keep approaching one another in the offers/counteroffers they propose which reduces the difference between the buyer's utility agreement and the seller's utility agreement.

In all the experimental results shown for the strategy **MSMM**, the seller agents' classi-



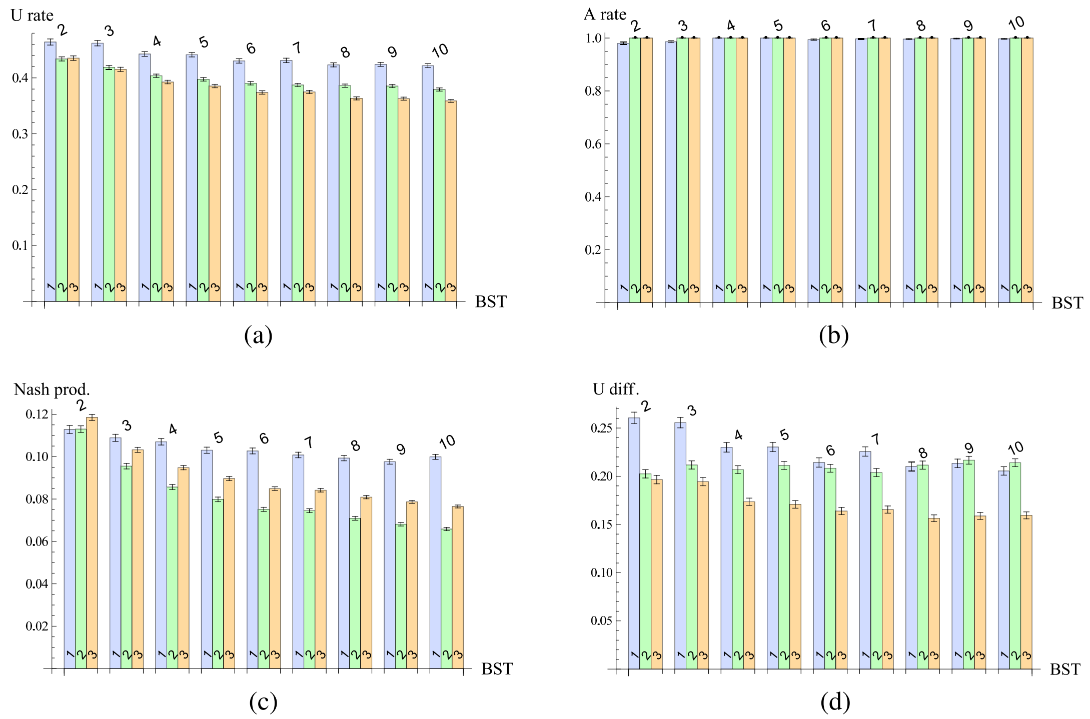
$(1 \rightarrow MSMM, 2 \rightarrow eCN, 3 \rightarrow GS)$

(*The numbers above the graph bars refer to the number of seller agents per object)*

Figure 6.4: *The buyer agents have shorter deadlines than the seller agents' deadlines and the number of seller agents per object varies.*

fication process is repeated at the start of each negotiation round except for the results shown in Figure 6.4. The results in Figure 6.4 show the results under the same experimental settings used for the experiments of Figure 6.3 except that the **MSMM** strategy classifies the seller agents at the start of the negotiation instance and do not update the classification later. The difference between the two classification schemes in terms of the utility rates is obvious, see Figures 6.3a and 6.4a. When the buyer agent reclassifies the seller agents at the start of each negotiation round, it gains recent knowledge about the new objectives and behaviors of the seller agents. In case the buyer agent classifies the seller agents once at the start of negotiation, the knowledge it gains becomes old and less effective as the negotiation process continues. Both classification schemes achieve similar results in terms of the agreement rates, see Figure 6.4b. However, the classification of the seller agents once at the start of negotiation results in better Nash product rates and better utility difference rates, see Figures 6.4c and 6.4d. The utility difference rates are similar to the utility difference rates produced by *GS* in most cases.

When the buyer agent seeks to secure high utility results, it needs to classify the seller agents at the start of every negotiation round. While if the buyer agent cares more about the social welfare and the fairness of the agreements, it should classify the seller agents once at the start of negotiation only. This conclusion applies when the seller agents use the time-dependent tactics to generate their offers. In all the following experimental results regarding the **MSMM** strategy, the buyer agent classifies the seller agents at the start of every negotiation round.



$(1 \rightarrow MSMM, 2 \rightarrow eCN, 3 \rightarrow GS)$

(*The numbers above the graph bars refer to the number of issues per object)*

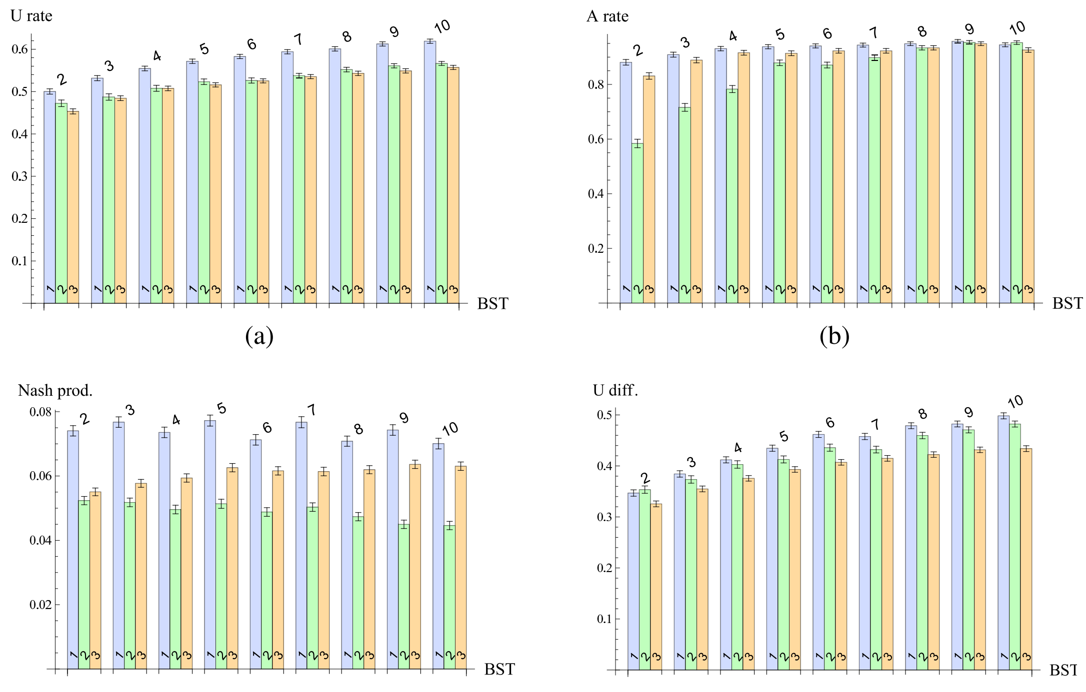
Figure 6.5: *The buyer agents have shorter deadlines than the seller agents' deadlines and the number of issues per object varies.*

The results when the buyer agents have shorter deadlines than the seller agents' deadlines and the number of issues per object varies are shown in Figure 6.5. The numbers on the top of the figure indicate the number of issues per object. The numbers start with 2 issues per object and increases gradually until 10 issues per object. For the specific experimental settings, see Table 6.2. As the number of issues per object increases, all strategies achieve gradually lower utility rates since the agents need to wait and keep conceding until they achieve the required utility for the object. However, Figure 6.5a shows that the **MSMM** strategy outperforms the other two strategies in terms of utility rate under all different number of issues per object. As before, the buyer agents have no problem in reaching agreements under the specified settings, see Figure 6.5b.

The Nash product results are shown in Figure 6.5c. When the number of issues per object is 2, the **MSMS** achieves lower Nash product rate than *GS* and similar to the *eCN* strategy. However, as the number of issues per object increases, the **MSMM** strategy outperforms the other two strategies. The reason is that when the number of issues increases, the **MSMM** strategy starts offering more utility values to its opponents since the **MSMM** strategy considers that agents have divergent preferences over issues when generating its counteroffers. The *eCN* strategy has the lowest Nash product rates. Figure 6.5d shows the utility difference results. The *GS* performs the best in terms of utility difference for the same reasons stated earlier. When the number of issues per object becomes large enough (> 7), the **MSMM** strategy performs similar or better than the *eCN* strategy since it starts offering its opponents more utility values that reduces the absolute difference between their utility agreements.

The experimental results when the buyer agents have longer deadlines than their opponents' deadlines are shown in Figure 6.6. Figure 6.6 shows the results when the number of seller agents per object varies. Since the seller agents have shorter deadlines, the seller agents approaches their reservation values before the buyer agents do. Accordingly, the difference in the utility rates between different strategies are not expected to be large, see Figure 6.6a. However, the **MSMM** strategy outperforms the other two strategies in all cases. Since the deadlines for the seller agents are shorter than the buyers' deadline, the seller agents offer their reservation values and quit negotiation before the buyer agents do. That can affect the agreement rates negatively, see Figure 6.6b. However, the **MSMM** strategy produces equal or better agreement rates than the other two strategies. When the number of seller agents per object is small, the *eCN* strategy performs the worst. The Nash product results show that the **MSMM** strategy outperforms the other two strategies in all cases as well, see Figure 6.6c. The *eCN* strategy produced the lowest Nash product rates because it is a competitive strategy that does not show any cooperation with its opponents.

The utility difference results presented in Figure 6.6d show that *GS* performs the best.



$(1 \rightarrow MSMM, 2 \rightarrow eCN, 3 \rightarrow GS)$

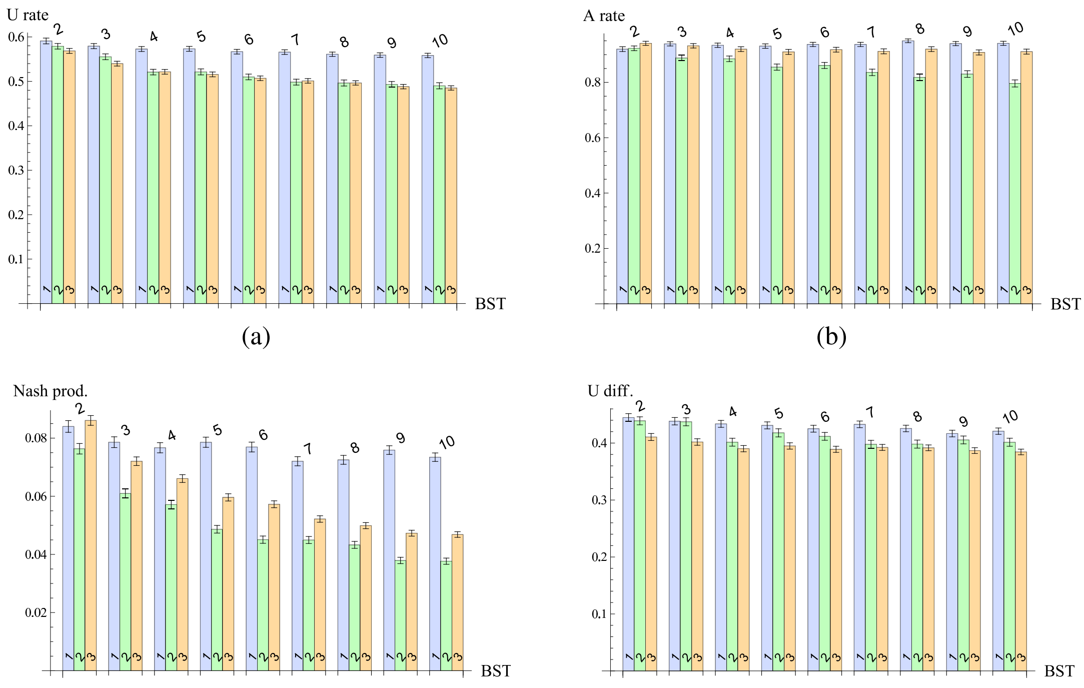
(*The numbers above the graph bars refer to the number of seller agents per object)*

Figure 6.6: *The buyer agents have longer deadlines than the seller agents' deadlines and the number of seller agents per object varies.*

In spite of the **MSMM** strategy outperforms the *eCN* strategy in terms of the utility rates, in many cases, there is no significant difference between the **MSMM** and *eCN* strategies in terms of the utility difference for the reasons stated earlier.

Figure 6.7 shows the experimental results when the buyer agents have longer deadlines than the seller agents' deadlines and the number of issues per object varies. As shown before, when the number of issues per object increases, the general trend is that the utility rates decreases for all strategies, see Figure 6.7. However, the **MSMM** strategy outperforms the benchmark strategies in all cases, see Figure 6.7a. The results of the agreement rates shown in Figure 6.7b are similar to the agreement rates shown in Figure 6.6b except for the *eCN* strategy where its agreement rates decreases when the number of issues per object increases. To a less extent, the same happens with *GS* while the **MSMM** strategy shows stability in the agreement rates.

The **MSMM** strategy outperforms the other two strategies in terms of Nash product



$(1 \rightarrow MSMM, 2 \rightarrow eCN, 3 \rightarrow GS)$

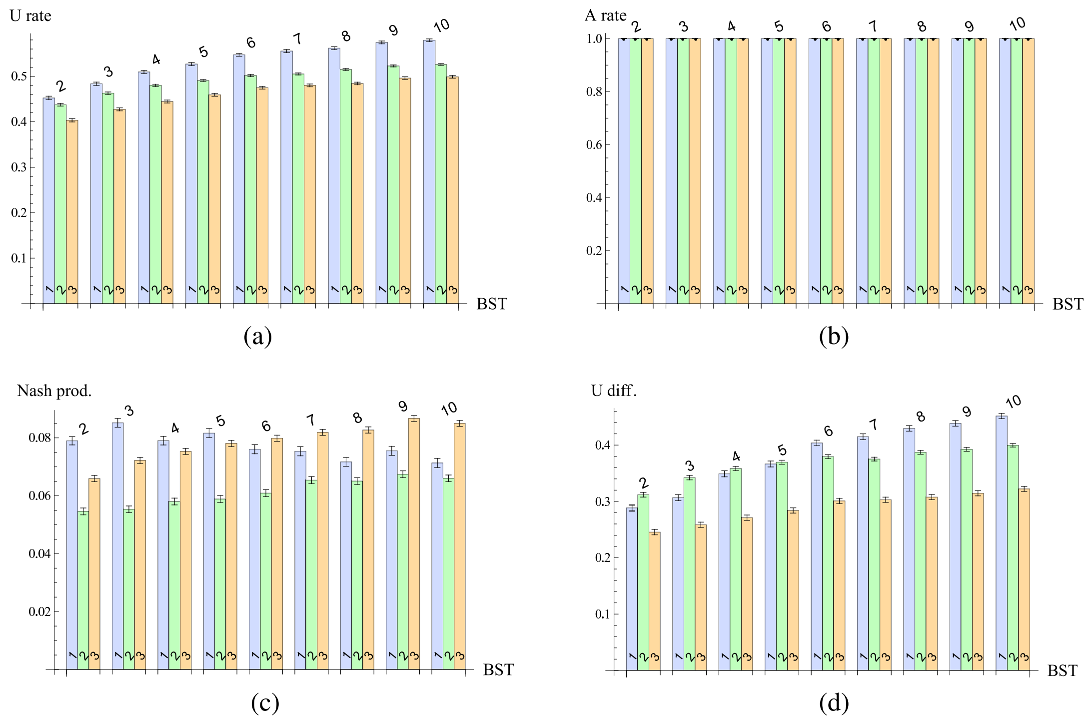
(*The numbers above the graph bars refer to the number of issues per object)*

Figure 6.7: *The buyer agents have longer deadlines than the seller agents' deadlines and the number of issues per object varies.*

rates, see Figure 6.7c. In addition, in many cases it performs similar to the *eCN* strategy in terms of the utility difference, see Figure 6.7d.

The last set of the experiments in this section is when all agents have equal deadlines. Starting with the results presented in Figure 6.8 where the number of seller agents per object varies, Figure 6.8a shows that the **MSMM** strategy performs better than the other two strategies and the *eCN* strategy comes next. Since all agents have equal deadlines, all buyer agents achieve 100% agreement rates, see Figure 6.8b.

When the number of seller agents per object is small, the **MSMM** strategy performs the best in terms of Nash product rates, see Figure 6.8c. When the number of seller agents per object increases, the **MSMM** strategy starts producing lower Nash product rates than the Nash product rates produced by *GS*. The reason is that when the number of seller agents per object increases, the **MSMM** strategy becomes more competitive and the result is lower Nash product rates. However, The **MSMM** produces better



$(1 \rightarrow MSMM, 2 \rightarrow eCN, 3 \rightarrow GS)$

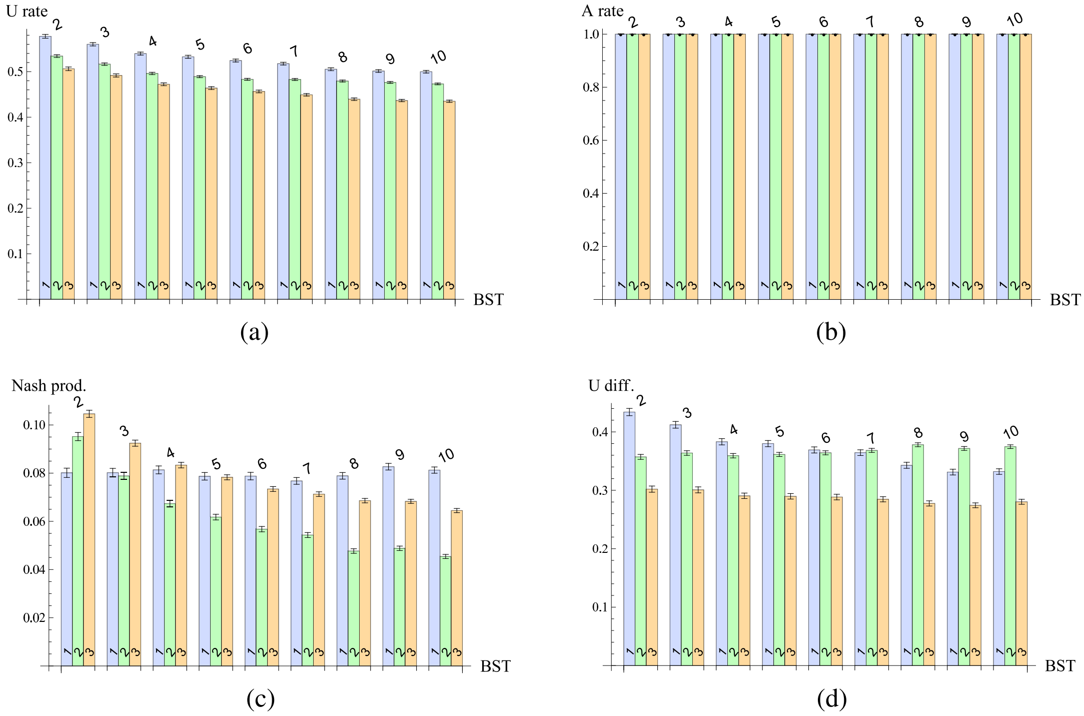
(*The numbers above the graph bars refer to the number of seller agents per object)*

Figure 6.8: *All agents have the same deadline and the number of seller agents per object varies.*

Nash product rates than the ones produced by the *eCN* strategy in all cases shown in Figure 6.8c.

The utility difference rates show that the **MSMM** strategy outperforms the *eCN* strategy when the number of seller agents per object is small, see Figure 6.8d. However, when the number of sellers per object increases, the **MSMM** strategy performs the worst since it becomes more competitive in the given settings. The *GS* performs the best in terms of the utility difference rates for the same reasons stated earlier.

Figure 6.9 shows the experimental results when the number of issues per object varies. The utility rates show the same trend as before, see Figure 6.9a. The **MSMM** strategy is also consistent to outperform the benchmark strategies. The results for the agreement rates are as in Figure 6.8b where all buyer agents achieve 100% agreement rates because all agents have equal deadlines and the agreement zones between the buyers and sellers exist, see Figure 6.9b.



$(1 \rightarrow MSMM, 2 \rightarrow eCN, 3 \rightarrow GS)$

(*The numbers above the graph bars refer to the number of issues per object)*

Figure 6.9: *All agents have the same deadline and the number of issues per object varies.*

When the number of issues per object is large (> 6), the **MSMM** strategy outperforms both, the *GS* and *eCN* strategies in terms of Nash product rates, see Figure 6.9c. The reason is the **MSMM** strategy offers its opponents more utility values when the number of issues per object is large, as a result, the Nash product rates are improved. Finally, the utility difference rates are shown in Figure 6.9d. When the number of issues per objects becomes large enough (> 6), the **MSMM** strategy outperforms the *eCN* strategy for the reasons stated earlier. In all cases, *GS* performs the best for the reasons explained before.

6.4.2.2 Testing under Different Agreement Zone Lengths

The specific experimental settings for testing the **MSMM** strategy when the agents have small and large overlap percentages between the reservation intervals of their negotiation issues are presented in Table 6.3. The agreement zones and the overlap percentages are used interchangeably.

Table 6.3: *Experimental settings of different agreement zone lengths*

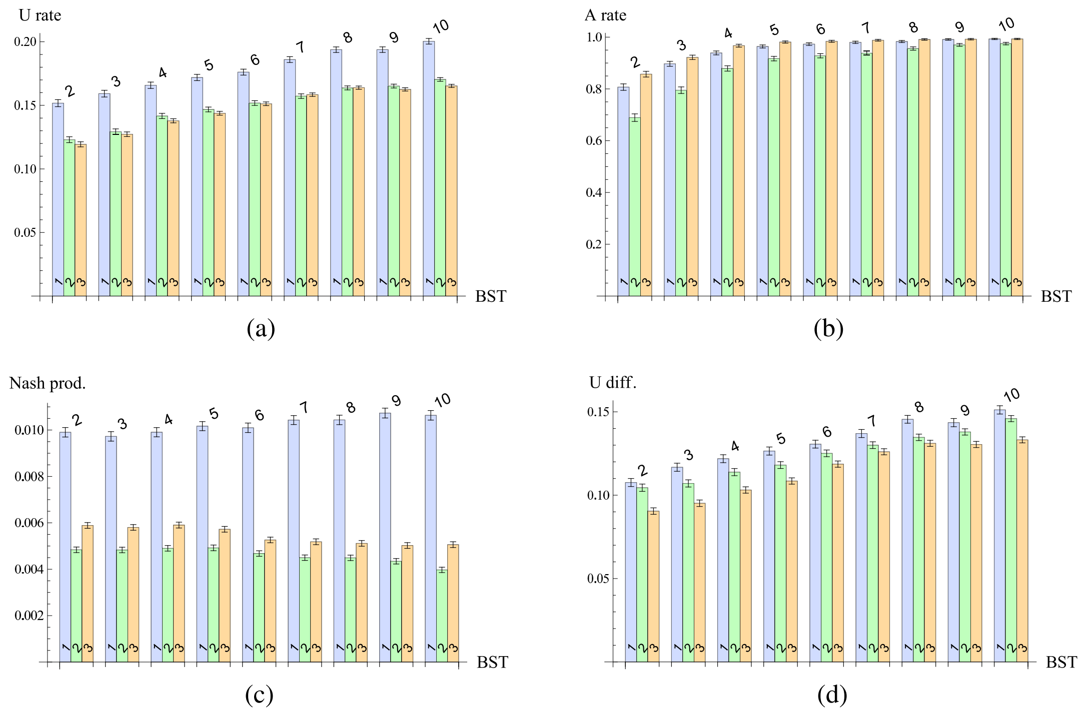
Agents or issues per object	Overlap description	Buyers' deadlines	sellers' deadlines	Buyers' beta value	sellers' beta values	Overlap	Figure name
Number of agents varies	Small overlap	[5-30]	[5-30]	[0.5-5]	[0.5-10]	5%-30%	6.10
Number of issues varies	Small overlap	[5-30]	[5-30]	[0.5-5]	[0.5-10]	5%-30%	6.11
Number of agents varies	Large overlap	[5-30]	[5-30]	[0.5-5]	[0.5-10]	70%-95%	6.12
Number of issues varies	Large overlap	[5-30]	[5-30]	[0.5-5]	[0.5-10]	70%-95%	6.13

In Table 6.3, a small overlap percentage is considered between 5% and 30% and a large overlap percentage is considered between 70% and 95%. When the overlap percentage in samll then the agreement zone is small and vice versa. For more information, see Section 4.5.2. When testing the performance of different strategies when the agreement zones are small, random overlap percentages are selected from the interval $[5\% - 30\%]$ for each issue where the seller agents can have different overlap percentages for the same issue. When testing for large agreement zones, the same procedure is used except that the interval of selection becomes $[70\% - 95\%]$.

In every negotiation round, each seller agent selects two random values from the intervals $[5 - 30]$ and $[0.50 - 10]$ for its deadline and β value respectively. In addition, two random values are selected randomly from the same intervals at the start of each negotiation round and assigned to the buyer agents as their deadline and β value respectively.

The first experimental results for testing different negotiation strategies when using small agreement zones between the buyer agents and the seller agents where the number of seller agents per object varies are shown in Figure 6.10. When negotiating agents have small agreement zones, agents need to reach near their reservation values before reaching an agreement. This results in low utility agreement rates for all agents. However, the **MSMM** strategy records better agreement rates than the other two strategies, see Figure 6.10a. As Figure 6.10a shows, when the number of seller agents per object increases, the buyer agents achieve higher utility rates. The negotiation strategies **MSMM** and *GS* achieve similar agreement rates while the *eCN* has lower agreement rates when the number of seller agents per object is small, see Figure 6.10b.

Even though the Nash product rates are small due to the low utility of an agreement for both, the buyer agents and the seller agents, the **MSMM** strategy outperforms the



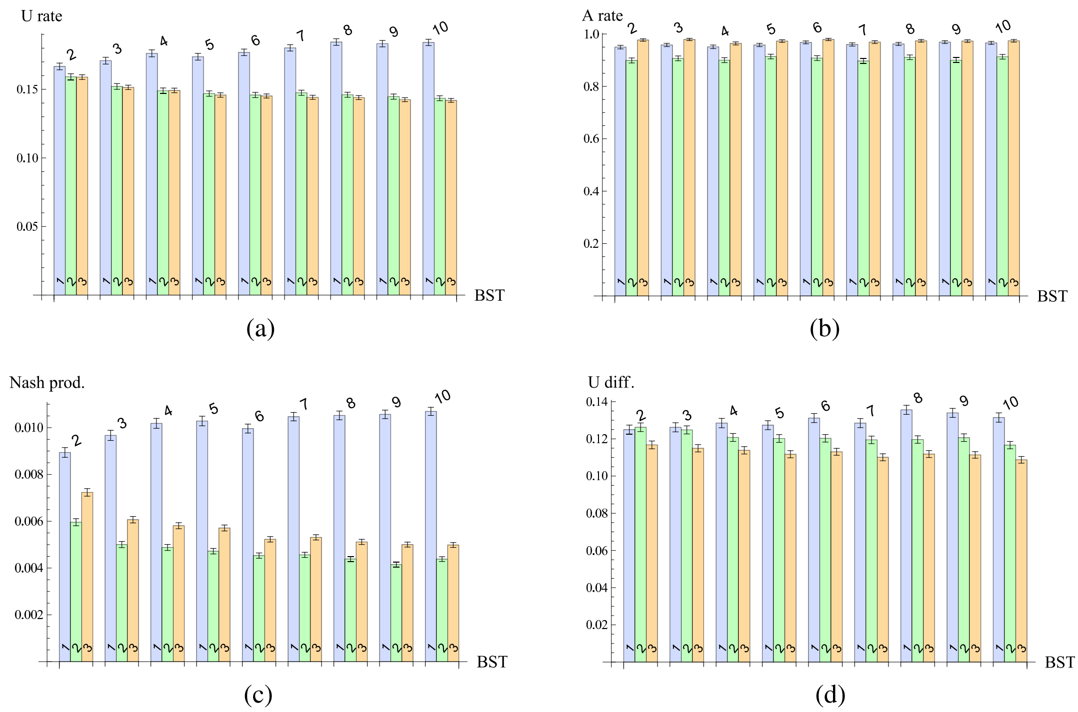
$(1 \rightarrow MSMM, 2 \rightarrow eCN, 3 \rightarrow GS)$

(*The numbers above the graph bars refer to the number of seller agents per object)*

Figure 6.10: *Agents have small overlap between their reservation intervals and the number of seller agents per object varies.*

other two strategies significantly, see Figure 6.10c. The utility difference rates show that the **MSMM** strategy performs the worst, see Figure 6.10d.

Figure 6.11 presents the experimental results when the number of issues per object varies while agents have small agreement zones. The utility results show that **MSMM** strategy outperforms the *GS* and *eCN* strategies in terms of utility rates as before, see Figure 6.11a. While the utility rates increase gradually for the **MSMM** strategy when the number of issues per object increases, the utility rates for the other strategies either decrease slightly or stay stable. The agreement rates archived by the **MSMM** strategy are similar to the agreement rates achieved by *GS* when the number of issues per objects becomes high, i.e., > 8, see Figure 6.11b. The agreement rates achieved by the *eCN* strategy are lower than the agreement rates achieved by the other strategies in the given negotiation settings since the *eCN* strategy is a competitive one and may not offer enough concessions which causes the presented results.

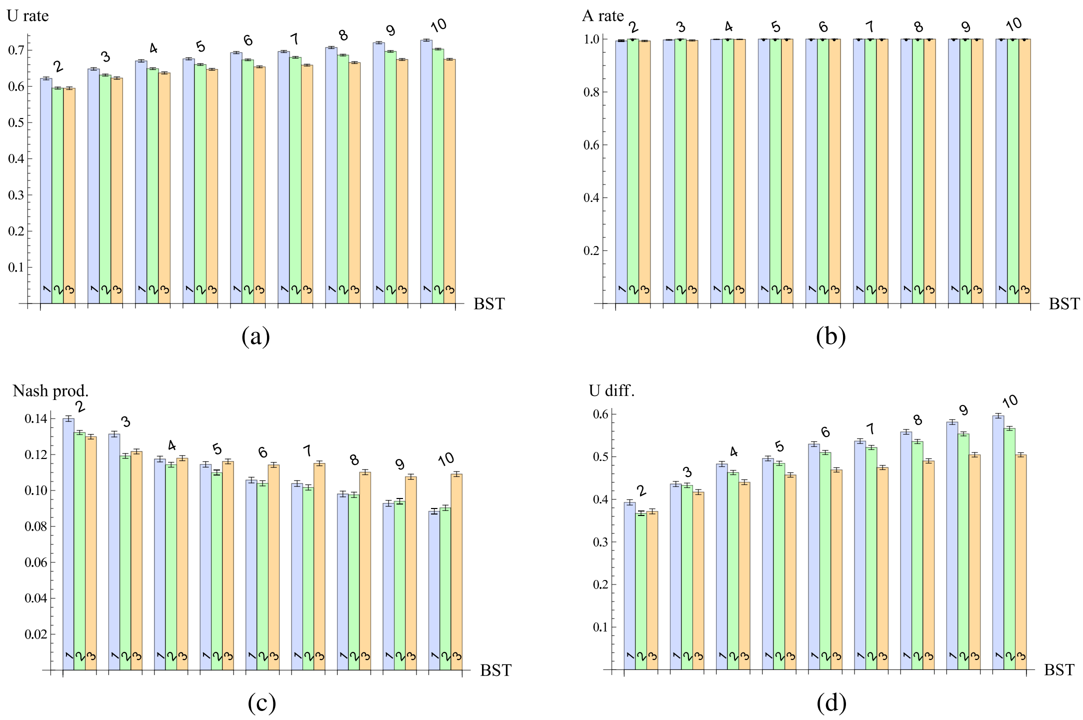


$(1 \to MSMM, 2 \to eCN, 3 \to GS)$
(*The numbers above the graph bars refer to the number of issues per object)*

Figure 6.11: *Agents have small overlap between their reservation intervals and the number of issues per object varies.*

The Nash product rates here are similar to the previous results, see Figures 6.10c and 6.11c. Since the number of seller agents is fixed here (see Section 6.4.2), the utility difference rates are relatively stable across different number of issues per object for all the buyer agents, see Figure 6.10d. In addition, the **MSMM** strategy shows higher utility difference than the other two strategies in all cases.

The next two sets of experiments show the results when the agreement zone lengths between buyers and sellers are large. Figure 6.12 shows the results when the number of seller agents per object varies. Larger agreement zones indicate a better negotiation environment. The buyer agents are able to achieve higher utility rates than in the previous set of experiments, see Figures 6.12a and 6.11a. In all cases, the **MSMM** strategy performs better than the other strategies in terms of utility rates, see Figure 6.12a. Since the agreement zones are large between agents, all the buyer agents have no problem in the agreement rates, see Figure 6.12b.



$(1 \rightarrow MSMM, 2 \rightarrow eCN, 3 \rightarrow GS)$

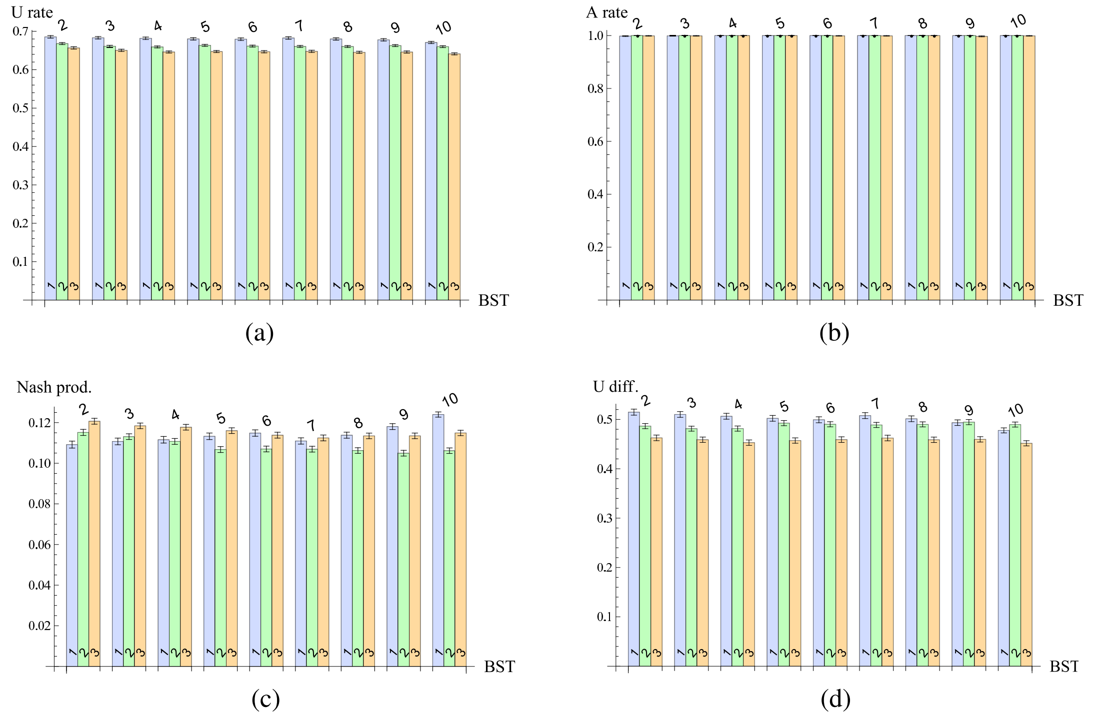
(*The numbers above the graph bars refer to the number of seller agents per object)*

Figure 6.12: *Agents have large overlap between their reservation intervals and the number of seller agents per object varies.*

When the number of sellers per object is less than 4, the **MSMM** strategy performs better than the other strategies in terms of the Nash product rates, see Figure 6.12c. However, when the number of sellers is beyond 4, the strategies **MSMM** and *eCN* perform similarly. The reason is that the **MSMM** strategy takes advantage of the situation when the number of sellers is large. When the number of sellers increases, all strategies produces lower Nash product rates. As Figure 6.12c shows, *GS* starts to perform better than the other strategies when the number of sellers per object is more than 4.

Again, the **MSMM** strategy produces the highest utility difference rates in most cases, see Figure 6.12d. As the case with the Nash product rates, when the number of seller agents per object increases, all strategies produces higher utility difference rates. As before, *GS* produces the lowest utility difference in most cases.

The last set of experiments in this section is presented in Figure 6.13 where agents have large agreement zones and the number of issues per object varies. Since the number of seller agents per object is fixed in all experiments, results show some stability in their behaviors. Figure 6.11 shows that the **MSMM** strategies performs better than the other two strategies in terms of utility rates, the *eCN* strategy comes next. As in the previous set of experiments, the buyer agents have no problem in the reaching agreements for the same reasons stated before, see Figure 6.13b.



$(1 \rightarrow MSMM, 2 \rightarrow eCN, 3 \rightarrow GS)$
(*The numbers above the graph bars refer to the number of issues per object)*

Figure 6.13: *Agents have large overlap between their reservation intervals and the number of issues per object varies.*

The **MSMM** strategy performs better than the other strategies in terms of Nash product rates when the number of issues per objects becomes more than 8. The reason is that when the number of issues per object becomes large, the **MSMM** strategy starts to offer their opponents proposals with higher values. When the number of seller agents per object is less than 8, the **MSMM** strategy performs either similar to the *eCN* strategy or to *GS*.

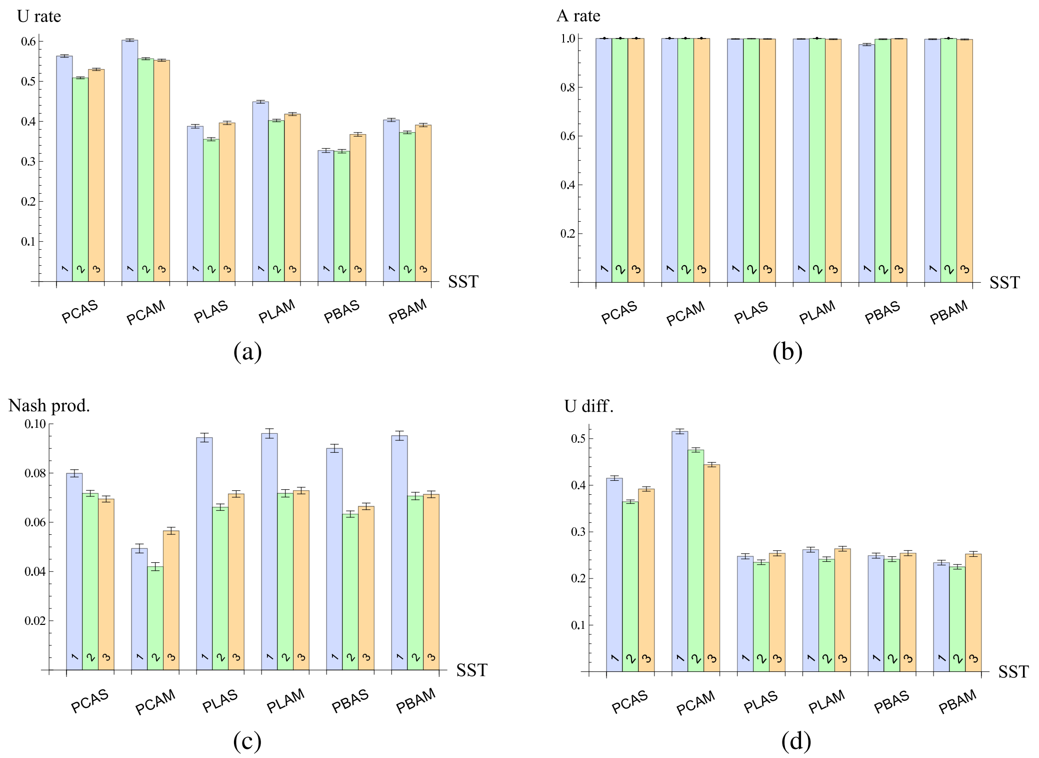
Finally, the **MSMM** strategy performs worse than the other strategies in terms of the utility difference rates when the number of seller agents per object is less than 9, after that, it performs similar or better than the *eCN* strategy, see Figure 6.13d.

6.4.2.3 Testing Against Mixed-Tactics Dependent Seller Agents

This section tests the performance of the **MSMM** strategy when the seller agents mix between the time-dependent tactics and the behavior-dependent tactics to generate their offers, see Sections 2.3.3.4 and 4.5.2. This sections shows two sets of results. The first one is when the number of seller agents per object is larger than the number of issues per object. The second set has the opposite settings. For the two sets of experiments, the following settings are used: at the start of each negotiation round, the deadlines and beta values are selected randomly for each seller agent from the intervals $[5, 30]$ and $[0.5, 10]$ respectively. Similarly, at the start of each negotiation round, two single values are selected randomly from the intervals $[5, 30]$ and $[0.5, 5]$ and assigned to the buyer agents as their deadline and β values respectively. Finally, random overlap percentages are selected from the interval $[0\% - 100\%]$ for each issue where the seller agents can have different overlap percentages for the same issue. In the follwoing experimental results, the *SST* label on the *x-axis* stands for the seller strategies.

The first letter in the names of the seller strategies (e.g., *PCAS*) that are shown on the *x-axis* in following experimental results stands for the type of the time-dependent function the seller agents use to generate the time-dependent part of the final offer, *P* stands for polynomial. The second letter stands for the type of the time-dependent tactic the seller agents use, it can be conceder (*C*), Boulware (*B*) or linear *L*. The third letter indicates that the seller agents use large portions of the last opponents' concession to generate the behavior dependent tactic, see Equation 2.9. The last letter indicates whether the total offer contains small (*S*) portion of the generated behavior-dependent offer in the final offer or medium (*M*) portion, for more information, see Section 4.5.2

The first experimental results where the number of seller agents per object is 10 and the number of issues per object is 5 are shown in Figure 6.14. Figure 6.14a shows that the **MSMM** strategy performs better than the other strategies in three cases, when the seller agents play *PCAS, PCAM* and *PLAM* while it shows similar utility rates as *GS* when the seller agents play *PLAS* and *PBAM* since the difference between them are not statistically significant.



$(1 \rightarrow MSMM, 2 \rightarrow eCN, 3 \rightarrow GS)$

Figure 6.14: *The number of seller agents per objects is larger than the number of issues per object.*

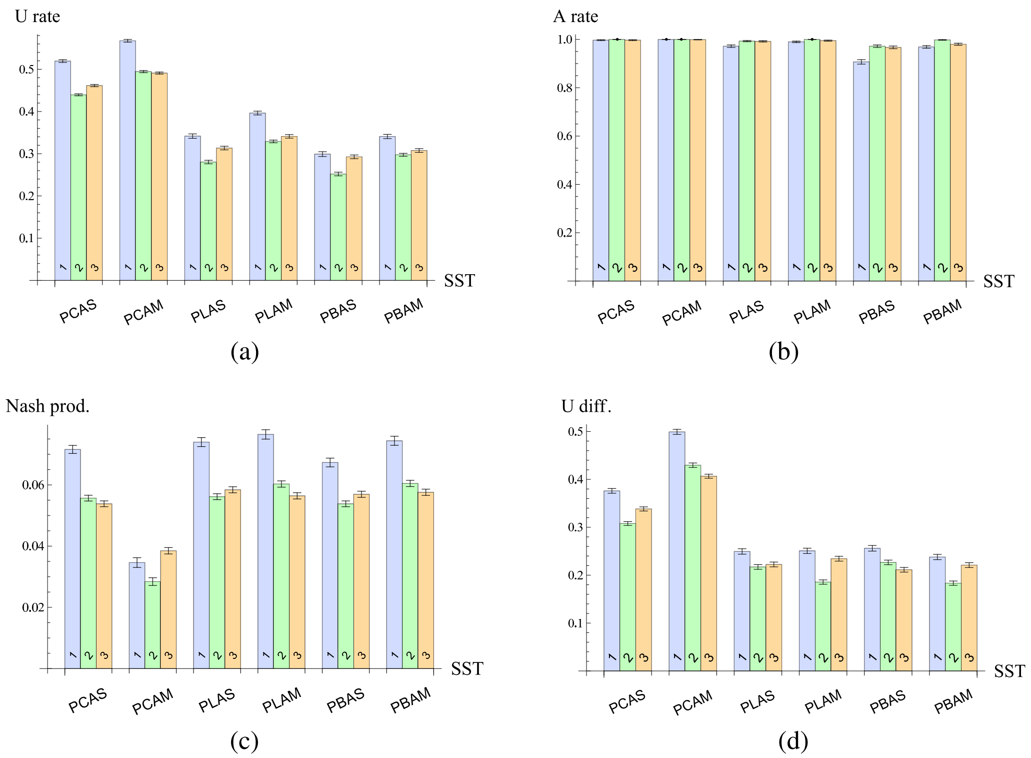
When the seller agents play *PBAS*, the **MSMM** strategy performs similar to the *eCN* strategy and less than *GS*. The *eCN* strategy shows the lowest performance in terms of utility rates. The reason is that the *eCN* strategy can have a problem in classifying the seller agents since the seller agents may show non-monotonic behavior when using the behavior-dependent tactic, this causes the *eCN* strategy to classify each seller agent as a non-conceder. The consequence of this classification is that the *eCN* strategy selects high β values that results in high concessions offers and lower utility rates are achieved. The reason that the **MSMM** strategy performs less than *GS* is also related to the classification scheme. However, the classification scheme of the **MSMM** strategy shows better performance than the classification scheme of the *eCN* strategy. With regard to the agreement rates, the buyer agent has no problem in reaching agreements in the given negotiation settings, see Figure 6.14b. The **MSMM** strategy shows a lower rate than the other strategies when the seller agents use the *PBAS* strategy. However, the agreement rate achieved by the **MSMM** strategy is still high ($> 95\%$).

The results for the Nash product rates show that the **MSMM** strategy outperforms the other strategies in all cases except where the seller agents use the *PCAM* strategy, see Figure 6.14c. In addition to the fact that the **MSMM** strategy offers its opponents more utility for its proposed counteroffers, it achieves high agreement utilities which improves the Nash product rates. The exceptional case in the results of the Nash product rates can be related to the fact that when the seller agents use the *PCAM* strategy, they offer large concessions in the offer generated by the time-dependent tactic which contributes a medium portion in the final offer. It means that the sellers may reach an agreement with a very small utility rate which affects the Nash product negatively.

Finally, Figure 6.14d shows the results for the utility difference rates. When the seller agents use the strategies PCAS or PCAM, the **MSMM** strategy produces the highest rates. When the seller agents use any of the other strategies, the **MSMM** strategies performs similar to *GS* or lower where both have higher utility rates than the *eCN* strategy. The reason is that the *eCN* concedes more than the other strategies for the reason stated in the previous paragraph which makes the difference in the agreement utilities between the buyers and the sellers small. Moreover, the utility difference rates for all buyer agents decreases sharply when the seller agents use the any of the following strategies: *PLAS, PLAM, PBAS, PBAM*. The reason is the seller agents tend to offer lower concessions that make the difference in utility smaller than when the seller agent use any of the other two strategies.

The second set of the experimental results where the number of seller agents per object is 5 and the number of issues per object is 10 is shown in Figure 6.15. The results in Figure 6.15 are better than the results shown in Figure 6.14a. The results of the utility rates here show that **MSMM** outperforms the other strategies in most cases and performs similar to *GS* in only one case, see Figure 6.15a. Since the number of issues per object in this experiments is higher than the ones in the previous experiments, the **MSMM** strategy can secure better utility rates. On the other hand, the **MSMM** strategy shows lower agreement rates in few cases, see Figure 6.15b. The reason is that the number of seller agents per object is lower than before which makes the classification process used by the **MSMM** strategy less adaptive in the given negotiation settings. Again, the agreement rates achieved by the **MSMM** strategy are still high ($\geq 95\%$).

The Nash product rates here are similar to the Nash product rates shown in Figure



$(1 \rightarrow MSMM, 2 \rightarrow eCN, 3 \rightarrow GS)$

Figure 6.15: *The number of seller agents per objects is smaller than the number of issues per object.*

6.14c, see Figure 6.15c: the **MSMM** strategy outperforms the other strategies except when the seller agents use the *PCAM* strategy in which *GS* records higher rates. The reason for that is explained above. One can note that the Nash product rates shown in Figure 6.15c are lower than the Nash product rates shown in Figure 6.14c. The reason is that the number of the seller agents per object in Figure 6.14c is 10 whereas the number of seller agents per object is 5 in Figure 6.15c. Consequently, the buyer agents are able to secure higher utility rates when the number of seller agents is high since it considered a favorable situation for the buyer agents.

Finally, the utility difference rates are shown in Figure 6.15d. The difference between the utility difference rates of the **MSMM** strategy and the other strategies are increased to some extent here when compared to the results shown in Figure 6.14d. Since agents are assumed to have divergent preferences over issues, the **MSMM** strategy can gain more utility per agreement and can also propose counteroffers with more utility to the opponents in every negotiation round. However since the buyer agent using the

MSMM strategy negotiates with multiple seller agents, it selects the best acceptable offer which increases the difference between the agreement utilities of the buyer and the seller agent.

6.4.2.4 Testing the IOG-conceder Agent

This section compares between the proposed **IOG-concession** tactic and *GS*. The *GS* is a concession type tactic that concedes on all the issues equally. On the other hand, the agent uses the **IOG-concession** tactic starts conceding on the *CMII* from the opponent's point of view, see Section 6.2.

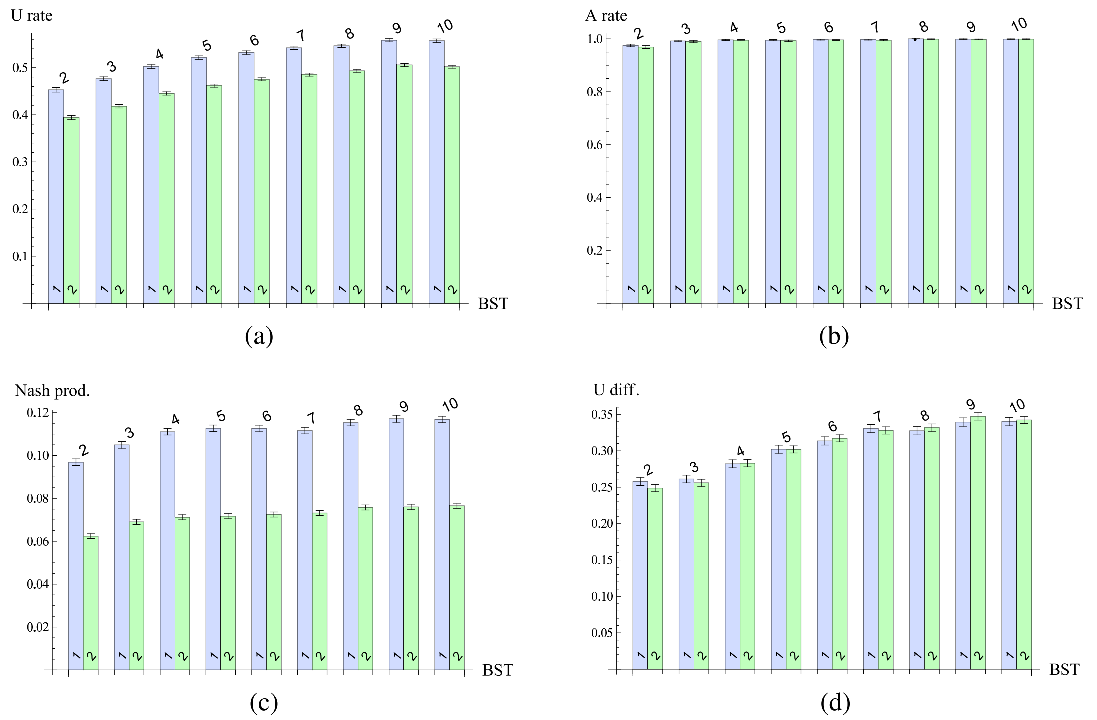
Table 6.4: *Experimental settings*

Agents or issues per object	Deadline description	Buyers' deadlines	sellers' deadlines	Buyers' beta value	sellers' beta values	Overlap	Figure name
Number of agents varies	Random deadlines	[5-30]	[5-30]	[0.5-5]	[0.5-10]	0%-100%	6.16
Number of issues varies	Random deadlines	[5-30]	[5-30]	[0.5-5]	[0.5-10]	0%-100%	6.17
Number of agents varies	Equal deadlines	[5-30]	[5-30]	[0.5-5]	[0.5-10]	0%-100%	6.18
Number of issues varies	Equal deadline	[5-30]	[5-30]	[0.5-5]	[0.5-10]	0%-100%	6.19

Table 6.4 shows the experimental settings used to generate different results in this section. It should be mentioned here that the buyer agent uses the **IOG-concession** tactic and the buyer agent uses *GS* propose two counteroffers in every negotiation round that have the same utility for both agents since they concede the same amount in terms of utility every time they generate their counteroffers. However, the values of the issues in the two composite counteroffers can be different, see Section 6.2.

Four sets of results are presented in this section (see Table 6.4) that represent different negotiation environments. The first set is shown in Figure 6.16. The first set shows the experimental results when the number of seller agents per object varies and the number of issues per object is as before, fixed and equals 5. In addition, each seller agent selects a random deadline from the interval $[5, 30]$ at the start of every negotiation instance. A deadline is also selected from the same interval at the start of each negotiation instance and assigned to the buyer agents. The overlap percentage is selected for each issue randomly form the interval [0%-100%] at the start of each negotiation instance too. The β values are selected as before.

The above experimental settings are used for all the experiments in this section. The difference between the settings of difference experiments are in the number of ob-



$(1 \rightarrow IOG - concession, 2 \rightarrow GS)$

(*The numbers above the graph bars refer to the number of seller agents per object)*

Figure 6.16: *The number of seller agents per object varies.*

jects/issues per object and the deadline which can be either randomly selected as explained before or be equal for all agents.

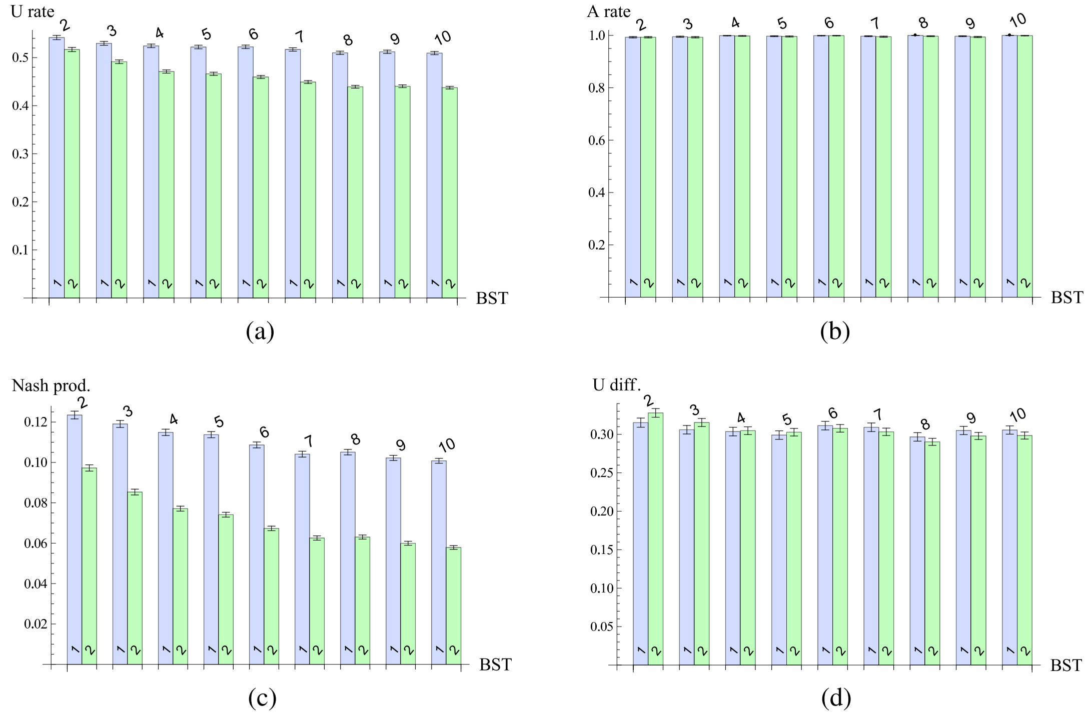
The utility rate results are presented in Figure 6.16a. The difference between the two negotiation tactics in the utility rates are obvious. The **IOG-concession** tactic performs better than *GS* because the **IOG-concession** generates counteroffers with higher utility values to its opponents than the counteroffers generated by *GS*. As a result, the **IOG-concession** tactic can reach an agreement faster than *GS*. Both agents concede at the same rate in terms of utility. If an agent can reach an agreement in negotiation round, for example, 7, then it can secure a better agreement utility than if it reaches an agreement at round 8. When the number of seller agents per object increases, the utility rates for both negotiation tactics increase since more opponents means better opportunity for the buyer agents to reach agreements with better utilities. The agreements rates for both buyer agents are the same, see Figure 6.16b.

The Nash product rates are shown in Figure 6.16c. The figure shows that the **IOG-**

concession tactic outperforms *GS* in all cases. The reason for that is the **IOG-concession** tactic gains higher utilities for the agreements than *GS*. In addition, the **IOG-concession** tactic provides better counteroffer utilities to its opponents. Both factors increase the Nash product rates for the **IOG-concession** tactic. Finally, the utility difference rates are shown in Figure 6.16d. The figure shows that both tactics achieve similar utility difference rates. From the results of the previous experiments, and in most cases, *GS* shows better performance in terms of the utility difference rates and since the two tactics are concession tactics, they are expected to achieve similar utility difference rates. As a final observation on the utility difference rates, when the number of seller agents per object increases, the utility difference rates for both buyer agents increase. When the number of seller agents is large, they have a better chance to select an agreement with a higher utility than when the number of seller agents per object is small.

The experimental results when the number of issues per object varies while the number of seller agents per object is fixed and equals 5 are presented in Figure 6.17. The **IOG-concession** tactic outperforms *GS* in terms of utility rates, see Figure 6.17a. When the number of issues per object increases, both tactics tend to gain less utility rate. The reason is that the buyer agents need to wait more time to reach the required utility for the object. Waiting for more time for a concession tactic means less agreement utility than before. However, when the number of issues per object increases, the difference between the two utility rates increases since the **IOG-concession** tactic can benefit from buyer agents and seller agents having divergent preferences over issues and not waiting for a longer time before reaching an agreement. In other words, the buyer agent using *GS* needs to wait more time than the **IOG-concession** tactic with every time the number of issues per object increases. Consequently, it results in bigger gaps between the utilities of the two tactics when the number of issues per object increases. As before, both tactics has the same agreement rate which is near 100% in all cases, see Figure 6.17b.

The Nash product rates are shown in Figure 6.17c. The figure shows that the **IOG-concession** tactic outperforms *GS* for the same reasons explained before. As shown in the figure, the Nash product rates decrease when the number of issues per object increases for both agents. The reason is that all agents (buyers and sellers) need to wait more time to reach an agreement which negatively affects the utility of the agreement for all agents. As the case with the utility rates results, the gaps between the Nash



$(1 \rightarrow IOG - concession, 2 \rightarrow GS)$

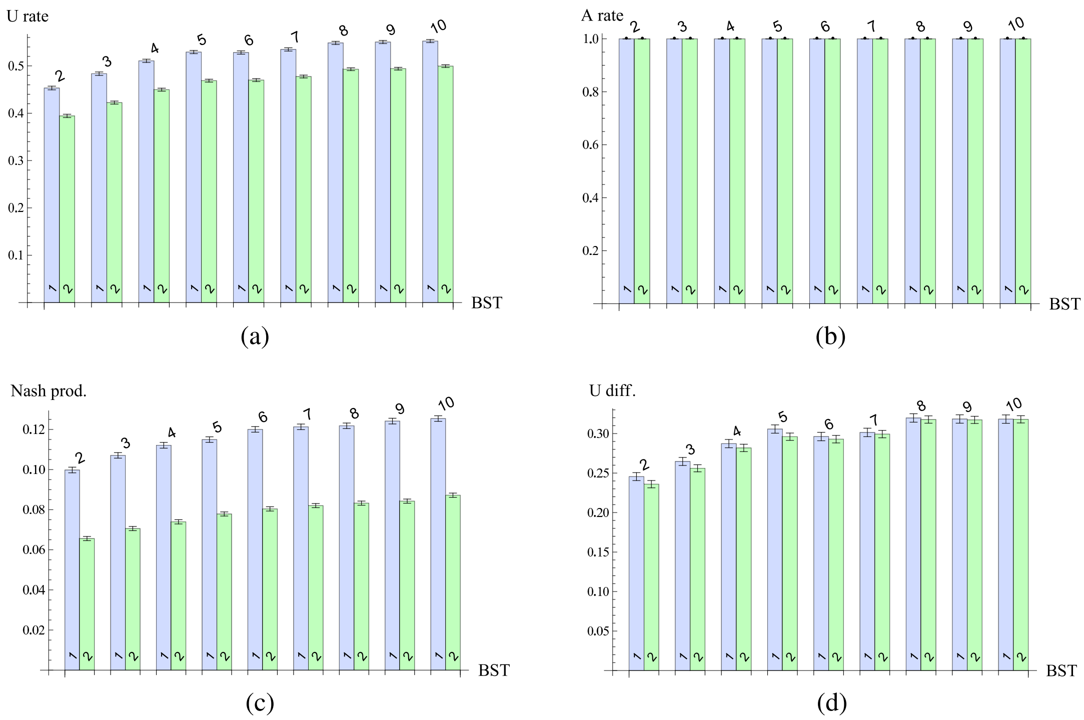
(*The numbers above the graph bars refer to the number of issues per object)*

Figure 6.17: *The number of issues per object varies.*

product rates for both buyer agents increase as the number of issues per object increases for the same reasons explained in the utility rates case.

Since the number of seller agents per object is fixed here, the utility difference rates are similar and stable for both tactics across the different number of issues per object, see Figure 6.17d. When the number of seller agents per object varies, the utility difference rates vary, see Figure 6.16d.

The third experimental set is shown in Figure 6.18 where all agents have equal deadlines and the number of seller agents per object varies. The results shown in Figure 6.18 are similar to the results shown in Figure 6.16, see figures (6.18a,6.16a), (6.18b,6.16b), (6.18c,6.16c) and (6.18d,6.16d). There is little difference in the agreement rates between the Figures 6.16b and 6.18b. Figure 6.18b shows that the buyer agents achieve 100% agreement rates whereas the buyer agents in Figure 6.16b miss few number of agreements because the negotiating agents can have different deadlines and conse-



$(1 \rightarrow IOG - concession, 2 \rightarrow GS)$
(*The numbers above the graph bars refer to the number of seller agents per object)*

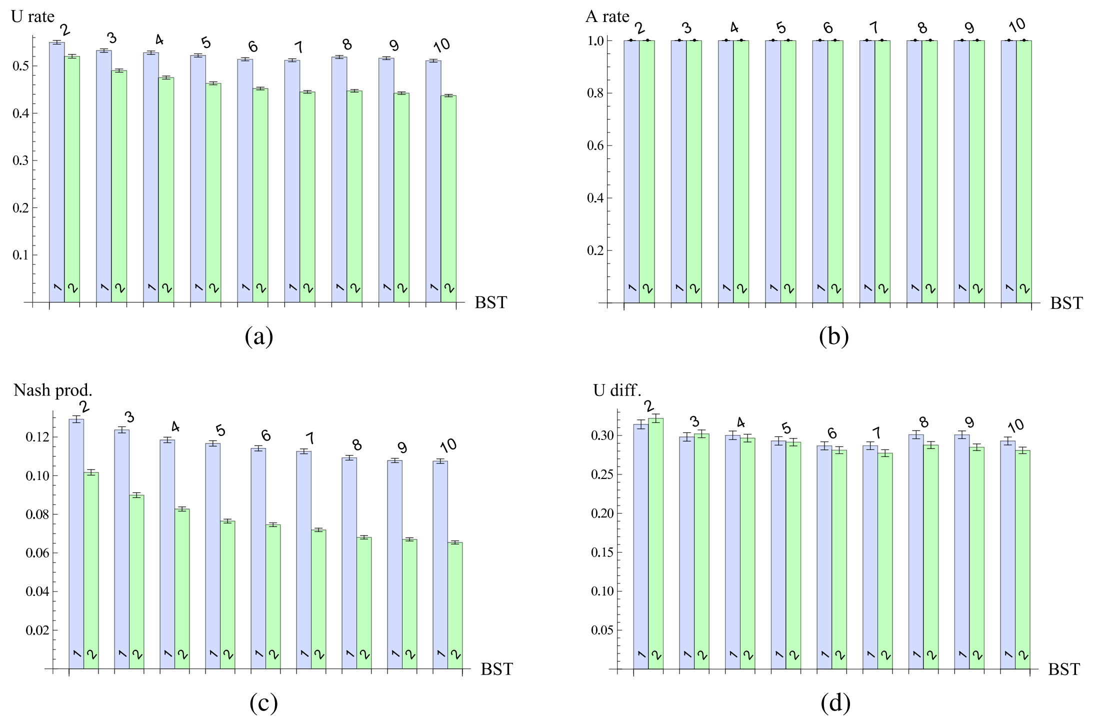
Figure 6.18: *The number of seller agents per object varies.*

quently, can miss reaching some agreements.

When all agents have equal deadlines, they offer their reservation values at their deadlines (like in Figure 6.18b) and since the agreement zone between agents exists for all issues, they must reach 100% agreement rates.

The reason behind the similarity between the results shown in Figures 6.16 and 6.18 is that when the deadlines for the agents are selected randomly in every negotiation instance, there will be an equal probability for the buyer agents to have shorter deadline than the seller agents's deadlines in the half of the number of the negotiation encounters and for having longer deadline in the other half. That applies also for a given negotiation instance, since the buyer agent may have longer deadline then half of the seller agents and can have shorter deadline than the second half of the seller agents. The overall results balance each other as if all agents have equal deadlines.

Finally, Figure 6.19 shows the results when all agents have equal deadlines and the



$(1 \rightarrow IOG - concession, 2 \rightarrow GS)$

(*The numbers above the graph bars refer to the number of issues per object)*

Figure 6.19: *The number of issues per object varies.*

number of issues per object varies. Again, the results shown in Figure 6.19 are similar to the results shown in Figure 6.17, see figures (6.19a,6.17a), (6.19b,6.17b), (6.19c,6.17c) and (6.19d,6.17d) . The reasons for this result are the same reasons that are explained in the previous paragraph.

6.5 Summary

This chapter investigates the coordination scenario where a buyer agent negotiates with multiple seller agents over an object characterized by multiple negotiation issues. Three main parts are presented in this chapter, the first part presents a novel offer generation mechanism, the Iterative Offer Generation **IOG**, that is used to generate counteroffers for one of the buyer agents in the experimental part. The second part is the meta-strategy coordination model. The last part is the empirical evaluation section that presents and analyzes the experimental results.

The **IOG** mechanism includes two negotiation tactics, the **IOG-trade-off** tactic and the **IOG-concession** tactic. Both tactics consider the preferences of the opponents when generating counteroffers. While staying on the current iso-curve, **IOG-trade-off** tactic offers more concessions on the issues that are believed to be more important to the opponents than the others. On the other hand, the **IOG-concession** tactic concedes in every negotiation round. It concedes more on the issues that are also believed to be more important to the opponents than others.

The meta-negotiation model classifies the seller agents into two sets: favorable set and unfavorable set. The model uses the **IOG-trade-off** tactic for generating counteroffers to the favorable set and uses the **IOG-concession** tactic for generating counteroffers to the unfavorable set. The **IOG-trade-off** tactic is used to reach an agreement with high utility while the **IOG-concession** tactic is used to guarantee an agreement. The buyer agent needs to move to a new iso-curve during negotiation when a deadlock is detected. Once a deadlock is detected, the buyer agent needs to choose new iso-curve with a lower aspiration level than before. Otherwise, the buyer agent can either reach an agreement with low utility (via the **IOG-concession** tactic) or not reaching an agreement at all.

The distance between the current ios-curve and the new iso-curve is determined by the lowest first-order difference in the utility offered in the last two negotiation round amongst the unfavorable group. The results show that when the buyer agent classifies the seller agents at the start of every negotiation round, the buyer agent gains more utility than if the seller agents were classified only once at the start of the negotiation instance.

The last part of the chapter presents and discusses the experimental results. The meta-strategy is tested with different deadline lengths and with different overlap percentages. In addition, it is tested against seller agents who mix between the time-dependent tactics and the behavior-dependent tactics when generating their offers.

The results show that the meta-strategy outperforms two benchmark strategies in terms of the utility rates and the Nash product rates. It also performs equal or better than the other strategies in terms of the agreement rates. In most cases, the meta-strategy produces higher utility difference rates than the other two strategies. In addition, it shows similar results when the seller agents use the mixed strategy to generate their offers. Moreover, the experimental results show the effect of negotiating with different numbers of seller agents per object and with different numbers of negotiation issues per object.

When the number of seller agents per object increases, all buyer agents produce higher utility rates, higher agreement rates, higher Nash product rates and higher utility difference rates. On other other hand, the buyer agents produce the opposite results when the number of issues per object increases.

The experimental results show that the **IOG-concession** tactic outperforms a benchmark concession negotiation tactic in terms of the utility rates and the Nash product rates when all agents select random negotiation parameter values (from the same intervals) including the deadlines. In addition, the experimental results show the same thing when all agents use equal deadlines while other negotiation parameter values are selected randomly from the same intervals. On the other hand, the two negotiation tactics show similar results in terms of the agreement rates and the utility difference rates. The experiments show similar results as before when the number of seller agents per object and the number of issues per object increase. Moreover, the results show that there is no significant difference in the results between using equal or random deadlines for agents.

The meta-strategy negotiation is used in the literature in bilateral negotiation. This section presents a novel negotiation mechanism that is effective in case of one-to-many negotiation. The main benchmark strategy that is used to validate the proposed meta-strategy depends on managing the convexity of the concession curves during negotiation.

Chapter 7

Multiple Objects with Multiple Negotiation Issues

This chapter investigates the coordination scenarios where the number of negotiation objects are multiple and the number of negotiation issues per object are multiple as well. Two coordination scenario mechanisms are proposed in this chapter: the multiple objects multiple issues and single provider (MMS) coordination mechanism and the global multiple objects multiple issues and multiple providers (MMM) coordination mechanism. Since there is a single provider per object in the MMS scenario, the coordination approach is based on managing the local reservation values for the common issues. The mechanism is tested under different negotiation environments and for different performance criteria. The experimental results prove that the proposed MMS coordination mechanism is effective and robust. On the other hand, the global MMM coordination mechanism populates the local reservation values based on the offers received from the opponents in the previous negotiation round. The experimental results show positive performance by the global MMM mechanism.

7.1 Introduction

Quality-of-service (QoS) attributes are the non-functional characteristics (e.g., throughput) of a service that distinguish between functionally equivalent services. Providers of functionally-similar services compete over the non-functional characteristics of services. A competitive criterion in the service oriented domain is the flexibility in the number of possible QoS attribute options that are available for customers to choose from. Consider a service with three customizable non-functional QoS attributes such as *throughput*, *execution time* and *availability*. If that service provider assigns three possible values for each attribute, then the total number of available configurations for that service is 27. If the number of service attributes and/or the number of possible values for each attribute increases then the number of possible service configuration increases and could be intractable. To keep the number of possible service configuration small, service providers assign small number of possible values for each service attribute. In case of service composition, the possible number of combinations becomes even larger and less attractable.

The current offer-based methods of QoS assignment show either little or no flexibility in the possible number of service configurations. An advantage of adopting automated negotiation as an approach for provisioning/procuring of services is that, when opponents exchange offers and counteroffers, they direct the search for possible QoS configurations towards their desired preferences by explicitly asking for specific values for the issues of each service.

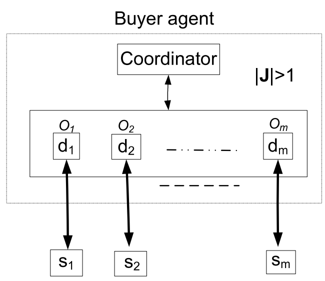


Figure 7.1: *One-to-many negotiation over multiple object with multiple issues*

This chapter investigates the coordination scenario where a buyer agent seeks to procure multiple objects where each object has multiple issues and a single provider, the **MMS** scenario. Figure 7.1 illustrates the **MMS** scenario. As explained previously, this situation exists in monopolistic markets where there is a single provider that controls the supply of a certain market item(s). Moreover, this chapter presents the coordination scenario where the buyer agent seeks multiple objects with multiple issues and multiple providers, which is a more common scenario than the **MMS** scenario. Figure 7.2

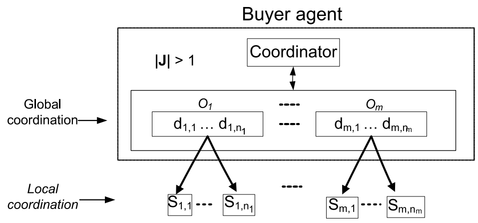


Figure 7.2: *Complex one-to-many negotiation*

illustrates the **MMM** scenario. The **MMM** is the most complex coordination scenario. Two coordination mechanisms are presented and validated: the **MMS** coordination scenario and the global **MMM** coordination scenario (**GMMM**).

7.2 MMS Coordination Approach

This section describes the proposed dynamic bidding strategy for the scenario shown in Figure 7.1, i.e., the **MMS** strategy. The buyer agent uses the information in each negotiation thread (i.e., $X^{t-1}_{d_{il} \leftrightarrow s_{il}}[J_i]$) in the decision making process of adjusting the weights in the initial **IW** matrix, see Table 7.1.

Table 7.1: *Local reservation value weights (*$\mathbf{IW}$*)*

	Service **A**	Service **B**	Service **C**	Service **D**	Total
$Price$	0.40	0.25	0.2	0.15	1
$Throughput$	0.42	0.32	0	0.26	1
$Response\_time$	0	0.4	0.25	0.35	1
$Reliability$	0.40	0.60	0	0	1

Table 7.2: *Local reservation values (*$\mathbf{LR}$*)*

	Service **A**	Service **B**	Service **C**	Service **D**	Global Reservation Values
$Price$	80	50	40	30	200
$Throughput$	21	16	0	13	50
$Response\_time$	0	16	10	14	40
$Reliability$	8	12	0	0	20

The proposed coordination strategy is dynamic since it utilizes the different concession behaviors (levels of cooperation) of the seller agents on each *common issue* (see Section 2.4.2) of each object to adapt the local reservation values for the *common issues* in real time, i.e., during negotiation. The **MMS** strategy adjusts the initial reservation value weights matrix that will be used to compute a possibly different local reservation value for each *common issue* of each service.

The initial reservation value weights matrix (see Table 7.1) could be initialized according to the initial reservation value of each issue. The initial reservation values are usually obtained from domain knowledge or from previous negotiations.

The **MMS** strategy involves 4 repetitive steps that are repeated in each negotiation round, see Algorithm 5.

Algorithm 5 MMS()

Require: $< X^{t-1}_{\mathbb{d}_{1,1}\leftrightarrow\mathbb{s}_{1,1}}[j], X^{t-1}_{\mathbb{d}_{1,2}\leftrightarrow\mathbb{s}_{1,2}}[j], ..., X^{t-1}_{\mathbb{d}_{1,\mathbb{n}_1}\leftrightarrow\mathbb{s}_{1,\mathbb{n}_1}}[j] >, ...,$
$< X^{t-1}_{\mathbb{d}_{\mathbb{m},1}\leftrightarrow\mathbb{s}_{\mathbb{m},1}}[j], X^{t-1}_{\mathbb{d}_{\mathbb{m},2}\leftrightarrow\mathbb{s}_{\mathbb{m},2}}[j], ..., X^{t-1}_{\mathbb{d}_{\mathbb{m},\mathbb{m}_\mathbb{n}}\leftrightarrow\mathbb{s}_{\mathbb{m},\mathbb{m}_\mathbb{n}}}[j] >$

```
while t <= t_max do
    GroupJ();
    Min_Max_Swap();
    Adjust_Weights();
    Adjust_Local_Res();
end while
```

In order to adjust the reservation value weights for the *common issues* dynamically during negotiation, we first need to get the recent concession vectors, i.e., the $F^{\{t-1,t\}}$, see section 4.3. The procedure **GroupJ()** returns the $F^{\{t-1,t\}}$ vector, where $[t-1, t]$ is the **CTI**, see section 4.3. The $F^{\{t-1,t\}}$ will be used by the next method, i.e., the **Min_Max_Swap()**.

The buyer agent starts applying its dynamic negotiation strategy after the first two negotiation rounds. After executing the **GroupJ()** algorithm, the **MMS** Algorithm executes the **Min_Max_Swap()** method, see Algorithm 6.

The **Min_Max_Swap()** algorithm runs into a number of iterations equals to $|K_i|/2$ and in each iteration, it swaps between the minimum and maximum values. In each new iteration, the previous exchanged values do not undergo a new exchange. In other words, in each iteration, the algorithm compares between the values that are not swapped in the previous iterations.

The idea behind the **Min_Max_Swap()** algorithm is to exploit the fact that different

Algorithm 6 Min_Max_Swap()

Require: $F^{\{t-1,t\}}$
for all $(K_i \in F^{\{t-1,t\}})$ **do**
  for $l = 1 \rightarrow (|K_i|/2)$ **do**
    $\Delta K_i^{'} = Swap(K_i)$
    $\Delta K_i = K_i^{'}$
  end for
end for
return $F^{\{t-1,t\}}$

seller agents can have different objectives. For example, some seller agents are desperate for reaching an agreement quickly by offering large amount of concessions while others prefer to reach an agreement that guarantees high utility and offer small amount of concessions during negotiation. When the difference between the offers of any two opponents is maximum, we exchange their values which guarantees that, in the next negotiation round, the more conceding seller agent receives a counteroffer with less concession than the counteroffer that will be generated for the less conceding seller agent. The purpose of this strategy is two folds: first, for agents who are conceding more, the buyer agent tries to secure an agreement with high utility, secondly, for the less conceding opponents, the buyer agent tries to secure an agreement regardless the utility gain as the main objective. The idea of the **Min_Max_Swap()** algorithm is explained following example.

- **Example:** assume that the K_i vector on issue j_i at time t is

  $K_i^t =< 60, 50, 55, 49, 45, 53, 65, 47 >$

  Now, we swap between the the minimum and maximum values in the set K_i^t over 4 iteration $(K_i^t|/2.)$ as follows:

  - 1st iteration:
    $(K_i^t)' =< 60, 50, 55, 49, \mathbf{65}, 53, \mathbf{45}, 47 >$
  - 2ed iteration:
    $(K_i^t)'' =< \mathbf{47}, 50, 55, 49, \mathbf{65}, 53, \mathbf{45}, \mathbf{60} >$
  - 3rd iteration:
    $(K_i^t)''' =< \mathbf{47}, 50, \mathbf{49}, \mathbf{55}, \mathbf{65}, 53, \mathbf{45}, \mathbf{60} >$

– 4th iteration:
$(K_i^t)'''' =< \mathbf{47}, \mathbf{53}, \mathbf{49}, \mathbf{55}, \mathbf{65}, \mathbf{50}, \mathbf{45}, \mathbf{60} >$

The value of k_i^t ($(K_i^t)''''$) in fourth iteration in the previous example is used by the **Adjust_Weights()** algorithm, see Algorithm 7. The coordination mechanism keeps a copy of the **IW** unchanged since the original **IW** is needed to control the maximum amount of change in the new generated local reservation value weights matrix (**W**). At the start of every negotiation round, the **W** equals the **IW**.

Algorithm 7 Adjust_Weights()

Require: **IW**
Require: K_i^t
W = IW
$THRESH_W = \mathbf{IW} - (\mathbf{IW} * \rho_1)$ *// in Exp.,* $\rho_1 = 0.3$
for all $(K_i \in F^{\{t-1,t\}})$ **do**
    $K_i' = K_i / max(K_i)$ *// normalize*
    $K_i = K_i'$
end for
for $i = 1 \to g$ **do**
    $\mathbf{W}[i,] = \mathbf{W}[i,] - (\Delta F_{j_i} / \rho_2)$ *// in Exp.,* $\rho_2 = 2$
end for
for $i = 1 \to g$ **do**
    for $l = 1 \to m$ **do**
        if $(|\mathbf{W}[i,l] - \mathbf{IW}[i,l]| \geq THRESH_W[i,l])$ **then**
            $\mathbf{W}[i,l] = \mathbf{IW}[i,l] + THRESH_W[i,l]$
        end if
        if $(|\mathbf{W}[i,l] - \mathbf{IW}[i,l]| < THRESH_W[i,l])$ **then**
            $\mathbf{W}[i,l] = \mathbf{IW}[i,l] - THRESH_W[i,l]$
        end if
    end for
end for
return W

In every negotiation round, a possibly new **W** matrix is generated and used to populate the local reservation value matrix for the common issues. The algorithm **Adjust_Weights()** normalizes the members of K_i^t and adjusts the weights in the **W** matrix, see Algorithm 7. The **IW** matrix is the initial weight matrix which is populated from domain knowledge or previous negotiation encounters. The **IW** matrix controls the maximum allowed change to the **W** matrix. Since different services can have different valuations for their issues (attributes), there should be a threshold for the maximum change. Once the new **W** is computed, the difference between the **IW** and **W** are adjusted. It is not expected that the initial **IW** varies beyond a certain amount in a given negotiation encounter, which is a realistic assumption. The parameter ρ_1 is used to control the variation amount, see Algorithm 7. A small ρ_1 value means a small variation is allowed and vice versa. In our experiment we use $\rho_1 = 0.3$. The parameter ρ_2 is used to determine the amount of change to each member in **W**.

Different ρ_2 are tested to find a value that produces good results in the given settings. As a result, the value of ρ in the experiments was chosen to be 2. The new generated **W** matrix is adjusted before its final use, see lines $10 - 19$ in Algorithm 7. Lines $10 - 19$ in Algorithm 7 are important to make sure that the weight of each issue does not differ from its value in **IW** beyond the threshold value.

The final step before generating the counteroffers by the buyer agent is to calculate the new local reservation values by multiplying the global reservation value of each issue by its new local reservation weight vector in the matrix **W**.

7.2.1 Experimental Results and Discussion

This section evaluates the coordination approach proposed for the **MMS** coordination scenario (see Figure 7.1) where a buyer agent seeks to procure multiple distinct objects (e.g., services) and each service has multiple issues while there are only one provider per service. The data shown in Tables 7.1 and 7.2 are used in the experiments of this section. Table 7.1 shows the local reservation weights for 4 services. Each service has at least two negotiation issues. Table 7.2 shows the global reservation values for each issue and the corresponding local reservation value for each issue using the weights in Table 7.1.

The buyer agent needs to reach an agreement over each object (connected agreement) to have a successful negotiation outcome. The buyer agents' utility weight vector used in the experiments is $\mathcal{W} =< 0.4,\ 0.25,\ 0.2,\ 0.15 >$ where the values of the vector correspond to the following issues in order: 1) price 2) throughput 3) response time 4) reliability. The two types of the buyer agents (the buyer agent using the **MMS** dynamic strategy and the buyer agent using the general strategy) use the same utility weight vector. The utility weight vector for each seller agent is calculated in the start of each negotiation encounter based on the reservation value of each issue, an issue with high reservation value gets a high weight.

Some of the negotiation settings in this section are also used in the empirical evaluation of Section 7.3. The negotiation environment of the experiments is described as follows:

- Offer generation tactics
    1. time-dependent tactics:
       All seller agents select a β value for the polynomial function [33] from the same distribution, $\beta \in [0.05, 10]$. The range of β value covers the three possible behaviors of an agent, i.e., Boulware where $\beta < 1$, linear where $\beta \approx 1$ and conceder where $\beta > 1$.
    2. tit-for-tat tactic:
       The random absolute tit-for-tat behavior-dependent tactic is used in the process of generating the mixed offers by the seller agents, $\delta = 1$ and $R(M) = 0$ [33]. The percentages of mixing between the time-dependent tactics and the random absolute tit-for-tat are presented later.
- the experiments compare between a buyer agent using one of the two proposed coordination strategies (**MMS** or **GMMM**) and a buyer agent using the general strategy (*GS*).
- at the start of each negotiation encounter which lasts for several rounds, both buyer agent types are assigned new negotiation parameters, e.g., deadlines. The non-strategic (i.e., *GS*) buyer agent keeps its negotiation parameters unchanged during negotiation while the strategic buyer agent (either using **MMS** or **GMMM**) adapts the local reservation values dynamically during negotiation according to the behaviors of the current seller agents in terms of their concessions.
- in each negotiation encounter, the two types of the buyer agents play against the same seller agents
- the error bars are shown for indicating the statistical significance of the results.
- if not stated, the used overlap percentages between the agents' reservation intervals are randomly selected from the interval $[0, 1]$.

The proposed **MMS** coordination strategy is tested under three different negotiation environmental factors: deadline, convexity of the concession curve and the type of the opponent.

7.2.1.1 Negotiation Deadline

Since negotiation deadline is an important negotiation factor given that negotiating agents must either accept the last received offer/counteroffer or quit negotiation by the end of their deadlines, deadlines can affect the negotiation outcome since they can affect both the possibility of reaching an agreement and the utility of an agreement. This section investigates the performance of the **MMS** strategy and *GS* under different deadlines.

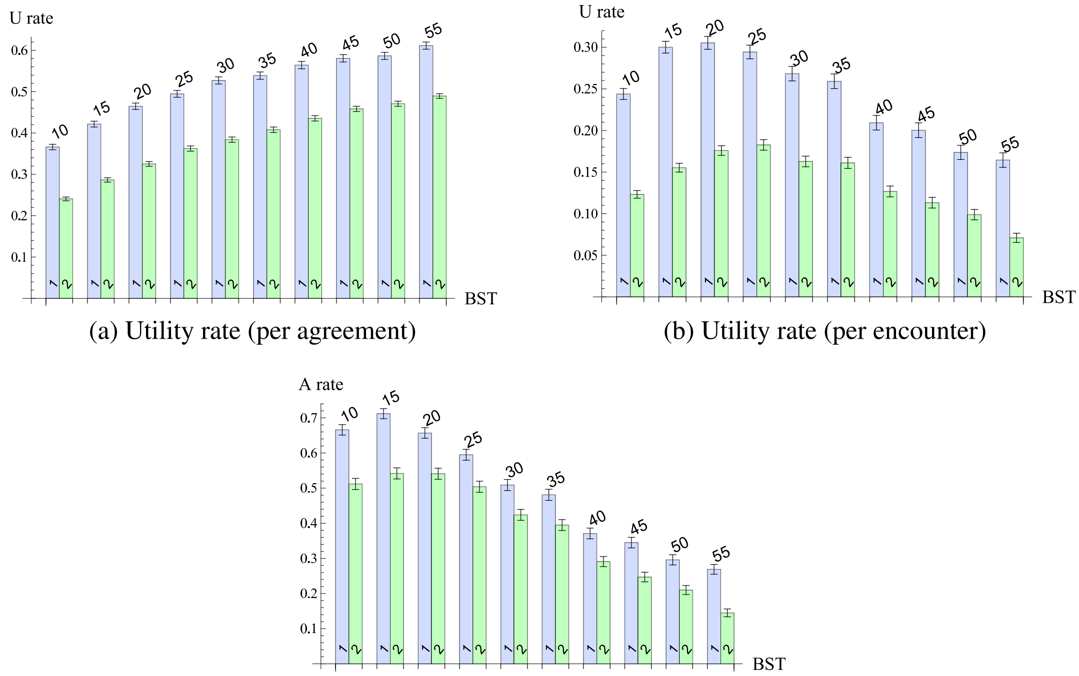
The settings of the experiments are summarized as follows:

- all agents use the time-dependent tactics to generate their offers/counteroffers.
- at the start of each negotiation instance, each seller agent selects a random deadline from the interval $[5, 60]$.
- at the start of each negotiation instance, the two types of the buyer agents use the same selected deadline and the same selected β value. The β value is selected from the interval $[0.05, 2]$.

The two types of the buyer agents are tested under 10 different deadlines and for each deadline, the experiment is repeated 1000 times. The term *negotiation encounter* here is used to indicate a negotiation attempt. For example, when the buyer agent needs to procure 4 objects, it needs to start 4 negotiation instances and keeps in negotiation until an agreement is reached or its deadline is reached. This marks the end of a negotiation encounter. It was important to clarify this point since the experimental results present most of the performance criteria as an average per agreement and as an average per encounter. The deadline set used in the experiments is $\{10, 15, 20, 25, 30, 35, 40, 45, 50, 55\}$. The deadlines are shown on the top of Figures 7.3 and 7.4. The chosen set of deadlines covers small, medium and large deadlines.

Two sets of experimental results are presented here. The first set is related to the utility rates and agreement rates. The second set is related to the Nash product rates and utility difference rates, see Section 6.4.2.

Figure 7.3 presents 3 types of results: utility rates per agreement, utility rates per encounter and agreement rates. As before, the *BST* label on the *x-axis* of the figures stands for the buyers' strategies.



(a) Utility rate (per agreement)

(b) Utility rate (per encounter)

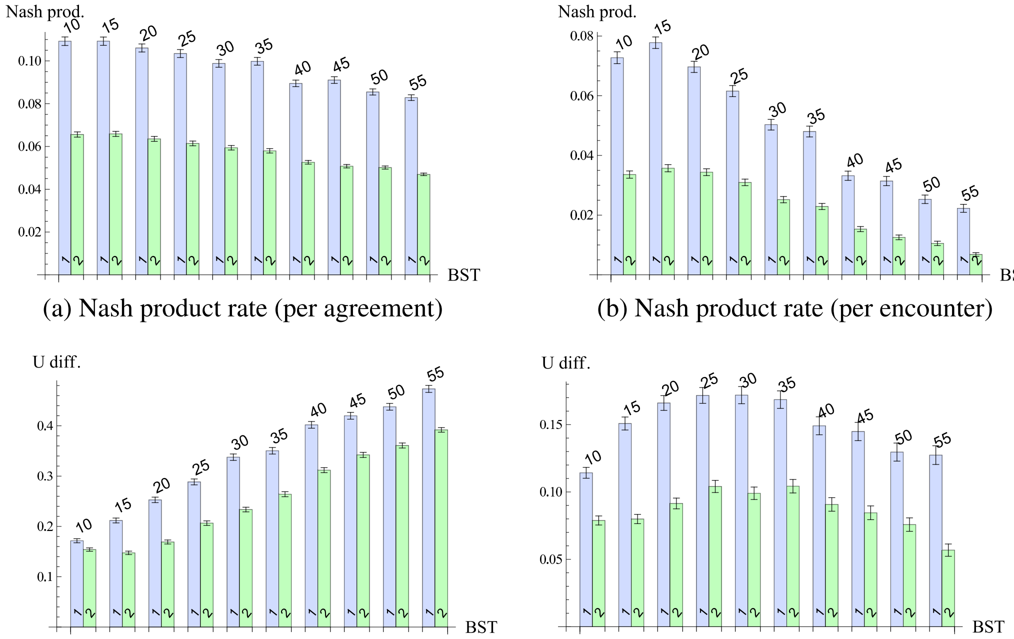
(c) Agreement rate

$(1 \rightarrow MMS\ strategy, 2 \rightarrow GS)$

(*The numbers above the graph bars refer to the buyer agents' deadlines)*

Figure 7.3: *The effect of different deadlines on the utility rate and the agreement rate*

Figures 7.3a and 7.3b show that the **MMS** strategy outperforms *GS* in terms of the utility rate per agreement and the utility rate per encounter across all deadlines. When the deadlines are short or large, the utility rates are relatively smaller than the utility rates when the deadlines are in the middle of the interval for both buyer agents, i.e., for the buyer agent uses the **MMS** strategy and the buyer agent uses *GS*. The reason is that when the buyers' deadlines are short or large, the seller agents' deadlines are selected short or large with small probabilities. As a consequence, the number of agreements are smaller because agents may reach their deadlines and quit negotiations without reaching an agreement. Since similar trends are shown in the following experimental results, this explanation is valid for all the following similar results.



(a) Nash product rate (per agreement)
(b) Nash product rate (per encounter)
(c) Utility Difference rate (per agreement)
(d) Utility Difference rate (per encounter)

$(1 \rightarrow MMS\ strategy, 2 \rightarrow GS)$
(*The numbers above the graph bars refer to the buyer agents' deadlines)*

Figure 7.4: *The effect of different deadlines on the Nash product rate and the utility difference rate*

Since the **MMS** strategy outperforms *GS* in the number of agreements, see Figure 7.3c, the total utility achieved by the **MMS** strategy is higher than the total utility achieved by *GS*. Accordingly, when dividing the total utilities by the number of encounters (1000 in our case), the differences in the utility rates per encounter between the **MMS** strategy and *GS* (see Figure 7.3b) are higher than their differences in case of the utility rates per agreement, see Figure 7.3a. The same explanation is valid when encountering similar results in the following experimental illustrations. Finally, the trend shown in Figure 7.3b is related to the results shown in Figure 7.3c.

The results shown in Figure 7.4 presents the Nash product rates and the utility difference rates. Figures 7.4a and 7.4b show the Nash product rate per agreement and the Nash product rate per encounter respectively. It is obvious that the **MMS** strategy outperforms *GS* across all different deadlines in terms of Nash product rate. The trend shown in Figure 7.4b is related to the results shown in Figure 7.3c.

The utility difference rate results are presented in Figures 7.4c and 7.4d. The **MMS** strategy shows higher utility difference rates in both figures. The results indicates that the fairness of the agreements is affected negatively when using the **MMS**.

The results above prove the effectiveness of the **MMS** strategy in managing the local reservation values of the common issues under different deadlines to achieve positive results in terms of the utility rate, the agreement rate and the Nash product rate.

7.2.1.2 Convexity of the Concession Curve

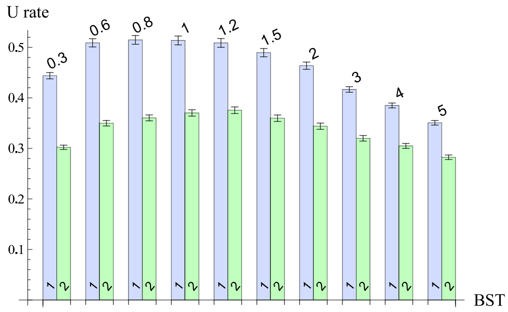
The convexity of a curve refers to the degree of its curvature. The convexity can affect the amount of concessions offered. Changing the convexity of a concession curve during negotiation affects the amount of concession offered at the next negotiation round. Experiments are designed and implemented to test the effect of different concession curve convexities on the performance of the buyers' strategies.

The experimental setups here are similar to the ones in Section 7.2.1.1 except for the buyers' deadlines and the β values. Since the β value determines the convexity of the concession curve, the two types of the buyer agents are tested under different β values. The set of β values used in the experiments is $\{0.3, 0.6, 0.8, 1, 1.2, 1.5, 2, 3, 4, 5\}$ which appears on the top of Figures 7.5 and 7.6. The set covers wide range of concession behaviors including tough, linear and conceder. A random deadline is selected from the interval $[5, 60]$ and assigned to the buyer agents at the start of every negotiation instance.

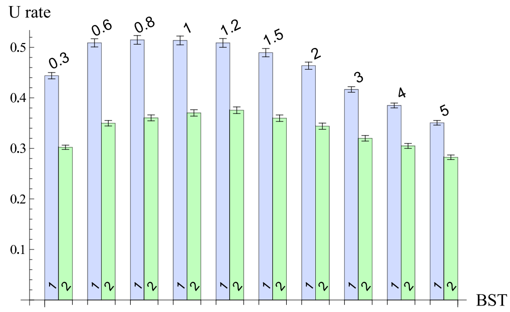
In the start of each negotiation instance, the two buyer agents use the same β value throughout negotiation and for each β value, the experiment is repeated 1000 times. As the case before, two experimental sets are presented in this section. The first set shows the utility rate and the agreement rate results while the second set shows the Nash product rate and the utility difference rate results.

The first set of the results are shown in Figure 7.5. The utility rate per agreement and the utility rate per encounter results are shown in Figures 7.5a and 7.5b respectively. The results show that the **MMS** strategy outperforms *GS* in terms of utility rate across all β values. Both buyer agents show lower utility rates when β values decrease. The reason is that with the increase in the values of β, the buyer agent offers more and more concessions. As a consequence, its utility per agreement gets smaller and smaller.

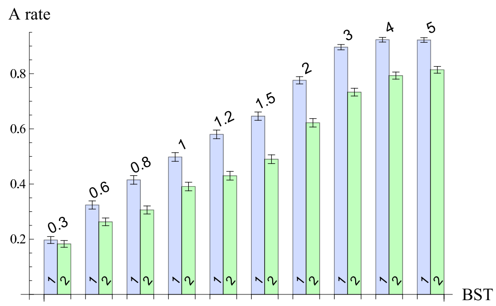
Figure 7.5c shows that the **MMS** strategy outperforms *GS* in terms of agreement rates across all β values.



(a) Utility rate (per agreement)



(b) Utility rate (per encounter)



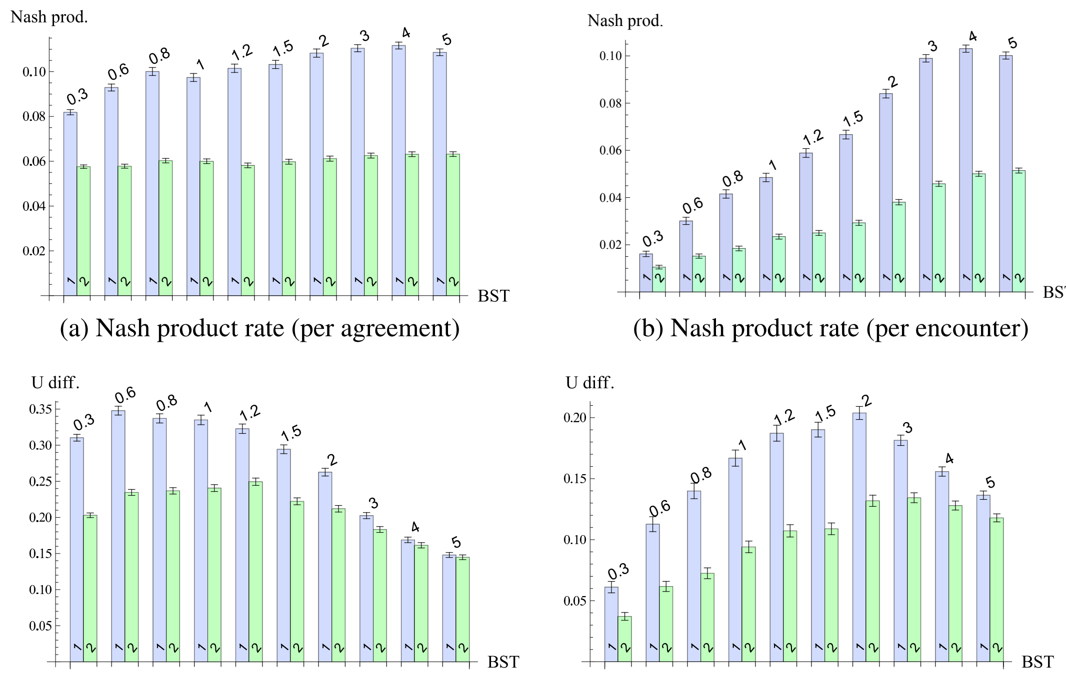
(c) Agreement rate

$(1 \rightarrow MMS\ strategy, 2 \rightarrow GS)$
(*The numbers above the graph bars refer to the buyers' β values)*

Figure 7.5: *The effect of curve convexities on the utility rate and the agreement rate*

The set experimental set is shown in Figure 7.6. Figures 7.6a and 7.6b show the Nash product rate per agreement and the Nash product rate per encounter results respectively. It is obvious that the **MMS** strategy outperforms *GS* in terms of Nash product rates across all β values. The results' trend in Figure 7.6b is related to the agreement rate results, see Figure 7.5c. On the other hand, Figures 7.6c and 7.6d show that the **MMS** strategy produces higher utility difference rates than *GS*. However, when the value of β becomes higher, both strategies perform similarly.

As the case with the deadlines, the results are consistent and the **MMS** strategy outperforms *GS* strategy in terms of utility rates and agreement rates across different concession curve convexities.



(a) Nash product rate (per agreement)

(b) Nash product rate (per encounter)

(c) Utility Difference rate (per agreement)

(d) Utility Difference rate (per encounter)

$(1 \rightarrow MMS\ strategy, 2 \rightarrow GS)$

Figure 7.6: *The effect of curve convexities on the Nash product rate and the utility difference rate*

7.3 MMM Coordination approach

This section investigates the scenario shown in Figure 7.2 where a buyer agent is negotiating with multiple seller agents over multiple distinct objects given that each agent has multiple issues and multiple providers. The situation for the buyer agent is more favorable in the case of the **MMM** scenario than the **MMS** scenario since there are many seller agents competing for each object. Algorithm 8 summarizes the proposed global coordination mechanism, the **GMMM** mechanism. The **GMMM** (**g**lobal **m**ultiple objects, **m**ultiple issues and **m**ultiple providers) mechanism does not require an initial **W** matrix (see Table 7.1) to start with in case the seller agents start proposing the offers. The matrix **W** for the next negotiation round is defined dynamically based on the received offers in the previous round.

The **GMMM** mechanism is explained as follows: first, it groups the last received

Algorithm 8 GMMM()

Require: *global reservation values vector*, **GRV**
Require: $< X^{t-1}_{\mathbb{d}_{1,1}\leftrightarrow\mathbb{s}_{1,1}}[j], X^{t-1}_{\mathbb{d}_{1,2}\leftrightarrow\mathbb{s}_{1,2}}[j], ..., X^{t-1}_{\mathbb{d}_{1,n_1}\leftrightarrow\mathbb{s}_{1,n_1}}[j] >, ...,$
$< X^{t-1}_{\mathbb{d}_{m,1}\leftrightarrow\mathbb{s}_{m,1}}[j], X^{t-1}_{\mathbb{d}_{m,2}\leftrightarrow\mathbb{s}_{m,2}}[j], ..., X^{t-1}_{\mathbb{d}_{m,m_n}\leftrightarrow\mathbb{s}_{m,m_n}}[j] >$
1: **for** $i = 1 \to m$ **do**
2: $\quad \mathcal{S}^t_{o_i} =< x^t_{s_{i,1}\to d_{i,1}}[J_1], x^t_{s_{i,2}\to d_{i,2}}[J_2], ..., x^t_{s_{i,n_i}\to d_{i,n_i}}[J_{n_i}] >$
3: **end for**
4: $\mathcal{S}^t =< \mathcal{S}^t_{o_1}, \mathcal{S}^t_{o_2}, ..., \mathcal{S}^t_{o_m} >$
5: $mv =<>;$
6: **for** $i = 1 \to m$ **do**
7: $\quad mv_i = findMeans(calMean(\mathcal{S}^t[i])$
8: $\quad add(mv, mv_i)$
9: **end for**
10: $TotalMeans = sum(mv)$ *// sum the means of each common issue*
11: $\mathbf{W} = mv/TotalMeans$
12: **LRV** $=$ **W** $\times$ **GRV** // **LRV** *stands for the local reservation values*
13: **return LRV**

offers from the seller agents over each object, see lines $1-3$ in Algorithm 8. The second step is to find the *mean* value of the received offers for each issue in each group $\mathcal{S}_{o_i}$, see lines $6-9$. For example, consider that the buyer agent receives multiple offers for service **A**, see Tables 7.1 and 7.2, then the mechanism finds the average received offer values for *price*, *throughput* and *reliability* issues since they are the issues that characterize service **A**. This procedure is performed on all the issues of the other services. The total sums of the common issues' means are calculated in line 10. Since the **W** matrix consists of the issues' weight vectors, the new vector weight for each common issue of each object is computed by dividing the mean value for each common issue of each object by the total sum of the means of the given common issue, see line 11. For example, if the total sum of the means for the price issue across all objects is $\{20 + 30 + 43 + 60\} = 153$ where the numbers *20, 30, 43* and *60* are the mean values for the prices received by the buyer agent from the providers of services **A**, **B**, **C**, and **D** respectively. The price weight vector for the negotiation objects in the next negotiation round is $\{20, 30, 43, 60\}/153 = \{0.130719, 0.196078, 0.281046, 0.392157\}$. Finally, the new price local reservation vector is multiplied by the remaining global reservation value of price. If the current price global reservation value is \$355, the new local reservation value for the price in the previous example is $\{0.130719, 0.196078, 0.281046, 0.392157\} * 355 =$

$\{46.4052, 69.6078, 99.7712, 139.216\}$. The previous vector can be interpreted as: the current price local reservation value for service **A** is $\$46.4052$ and the current price local reservation value for service **B** is $\$69.6078$ etc. This process is repeated for the other issues. As line 12 shows, the new **W** matrix is multiplied by the vector of the remaining global reservation values **GRV**. The local reservation (**LR**) matrix is returned by the algorithm. Finally, the buyer agent uses possibly a new local reservation value for each issues of each object in every negotiation round as the algorithm is repeated at the start of every negotiation round.

Since the buyer agent receives multiple offers for each issue, then taking the *mean* value for the received offers and then normalizes all the mean value vectors for all issues provides a good approximation for the demand and importance of each issue to a particular seller group. Consequently, the dynamic adaptation of the **W** matrix responds to the behaviors of the seller agents in terms of their concessions on various issues.

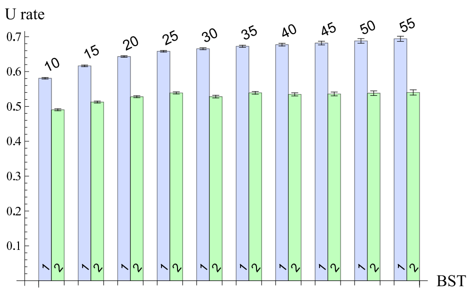
The proposed mechanism in Algorithm 8 is one of the possible ways for coordinating the bidding strategy at the global level in the given scenario. However, other mechanisms that work under different assumptions need to be designed and tested. For example, in case the buyer agent has an initial local reservation weight matrix and the amount of resource shifting between delegates cannot go beyond a certain amount for each issue, then the shifting of resources according to the behaviors of the seller agents over the common issues amongst delegates is the suitable approach in this case. In addition, a local coordination mechanism is essential for using a hybrid coordination mechanism since the empirical results in Chapter 5 show that the hybrid coordination mechanism outperforms other coordination mechanisms in terms of the utility rates and the agreement rates.

7.3.1 Experimental Results and Discussion

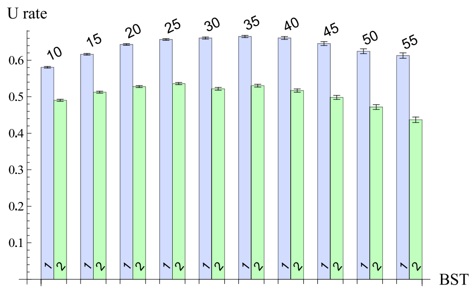
This section tests the **GMMM** strategy under four negotiation variables: deadline, convexity of the concession curve, number of available seller and finally length of the agreement zone.

7.3.1.1 Negotiation Deadline

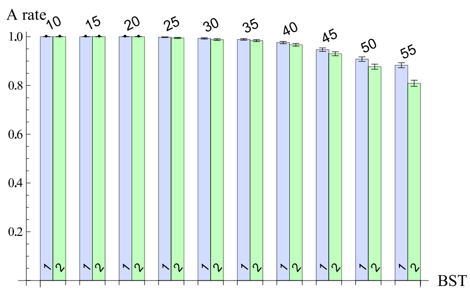
The experimental settings here are similar to the settings mentioned in section 7.2.1.1. The difference here is that the number of the seller agents per object is set to 5. The numbers shown above bars in the following graphs indicate the buyer agents' deadlines. The seller agents select their deadlines as explained in section 7.2.1.1.



(a) Utility rate (per agreement)



(b) Utility rate (per encounter)



(c) Agreement rate

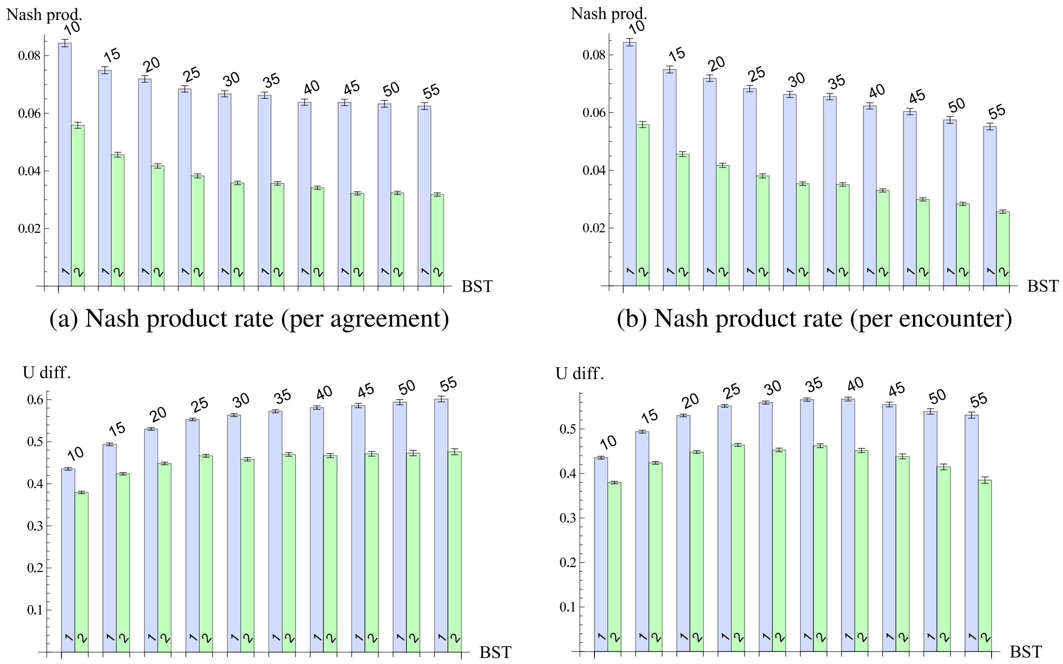
$(1 \rightarrow GMMM\ strategy, 2 \rightarrow GS)$
(*The numbers above the graph bars refer to the buyer agents' deadlines)*

Figure 7.7: *The effect of different deadlines on the utility rate and the agreement rate*

The first set of results is shown in Figure 7.7. Figures 7.7a and 7.7b show that the **GMMM** strategy outperforms *GS* significantly in terms of the utility rate per agreement and the utility rate per encounter results. Since the number of the providers per object are multiple, achieving a good agreement rate is not a problem for both strategies, see Figure 7.7c. Since the number of the seller agents per object is multiple in the **MMM** scenario, it is expected that the buyer agents benefit from the situation and gain higher utility rates than in the **MMS** scenario, see Figures 7.3a and 7.7a.

The Nash product rate and the utility difference rate results are presented in Figure

7.8. Figures 7.8a and 7.8b show that the **GMMM** strategy outperforms *GS* strategy in terms of Nash product rates. The results' trends shown in Figures 7.8a and 7.8b can be justified by the fact that when the buyer agents have long deadlines, the agreement rates can be affected negatively (as explained earlier) and the utility of the opponents can be very small.



(a) Nash product rate (per agreement)

(b) Nash product rate (per encounter)

(c) Utility Difference rate (per agreement)

(d) Utility Difference rate (per encounter)

$(1 \rightarrow GMMM\ strategy, 2 \rightarrow GS)$

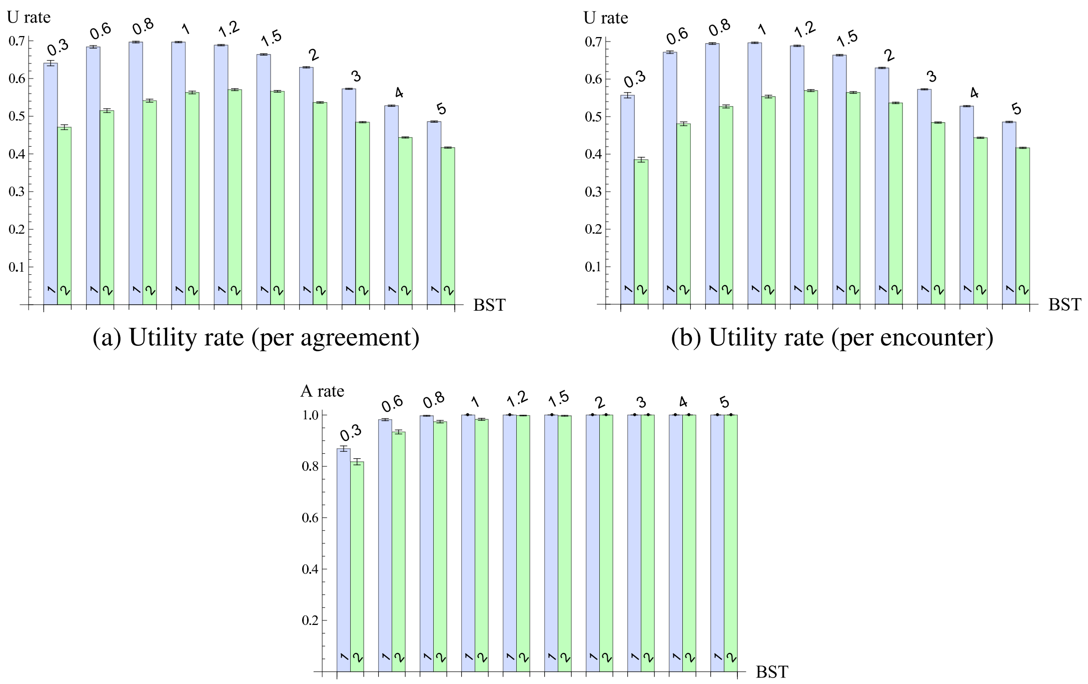
(*The numbers above the graph bars refer to the buyer agents' deadlines)*

Figure 7.8: *The effect of different deadlines on the Nash product rate and the utility difference rate*

The utility difference rate per agreement and the utility difference rate per encounter results are presented in Figures 7.8c and 7.8d respectively. The utility difference rates for the buyers increase when their deadlines increase. The reason is that when the buyers' deadlines are longer than the sellers' deadlines, the gaps between their utilities increase since the seller agents offer their reservation values before their counterpart buyer agents. As before, the **GMMM** strategy shows higher utility difference rates than *GS* does.

7.3.1.2 Convexity of the Concession Curve

The settings here are similar to the setting in section 7.2.1. Again, the difference is that buyer agents use a certain β value in each negotiation encounter while all other parameters are selected randomly as explained earlier. Changing the convexity of the concession curve affects the amount of concession offered at a particular round.



(a) Utility rate (per agreement)

(b) Utility rate (per encounter)

(c) Agreement rate

$(1 \rightarrow GMMM\ strategy, 2 \rightarrow GS)$

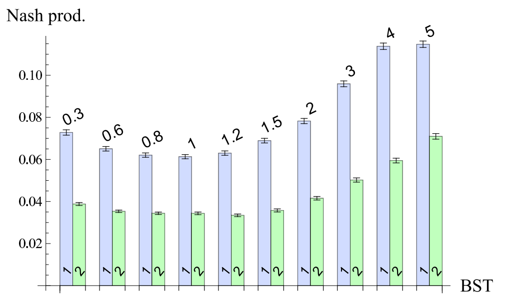
(*The numbers above the graph bars refer to the buyers' β values)*

Figure 7.9: *The effect of different buyers' β values on the utility rate and the agreement rate*

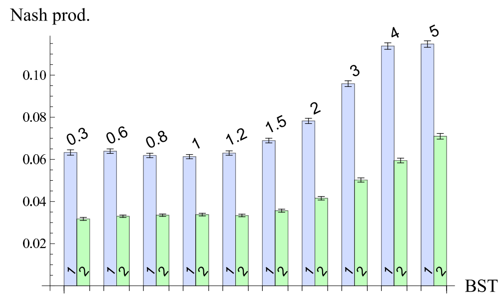
To test the effect of using different convexity degrees for the buyers' concession curve, we test the proposed strategy under different curve convexities. The value β in the time dependent-offer generation tactic affects the convexity of the concession curve. The values of β used in the experiments are shown on the top of Figures 7.9 and 7.10.

The results in Figure 7.9 show that the **GMMM** outperforms *GS* in terms of the utility rate per agreement (see Figure 7.9a) and the utility rate per encounter, see Figure 7.9b.

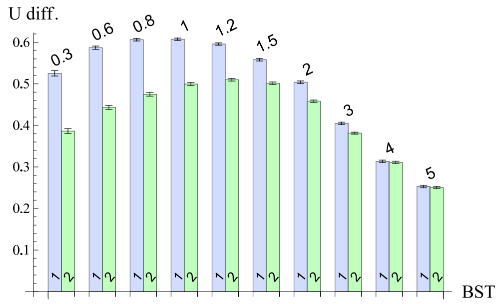
When the β values become large, the utility rates for the buyer agents decrease. However, the **GMMM** outperforms *GS* in all cases. Both strategies perform similarly in terms of the agreement rate (see Figure 7.9c) since the number of the seller agents per object is multiple and the chance of reaching an agreement is high. When the buyer agents have very small β values, they miss some agreements since they concede in very small amounts which makes reaching an agreement more difficult. However, the **GMMM** performs similar or better than *GS* in all cases.



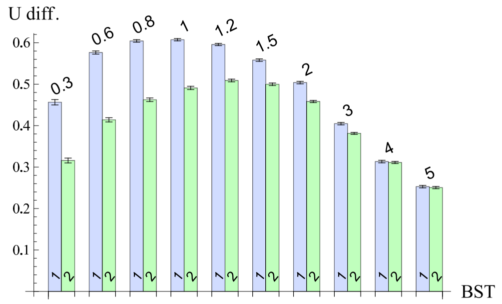
(a) Nash product rate (per agreement)



(b) Nash product rate (per encounter)



(c) Utility Difference rate (per agreement)



(d) Utility Difference rate (per encounter)

$(1 \rightarrow GMMM\ strategy, 2 \rightarrow GS)$
(*The numbers above the graph bars refer to the buyers' β values)*

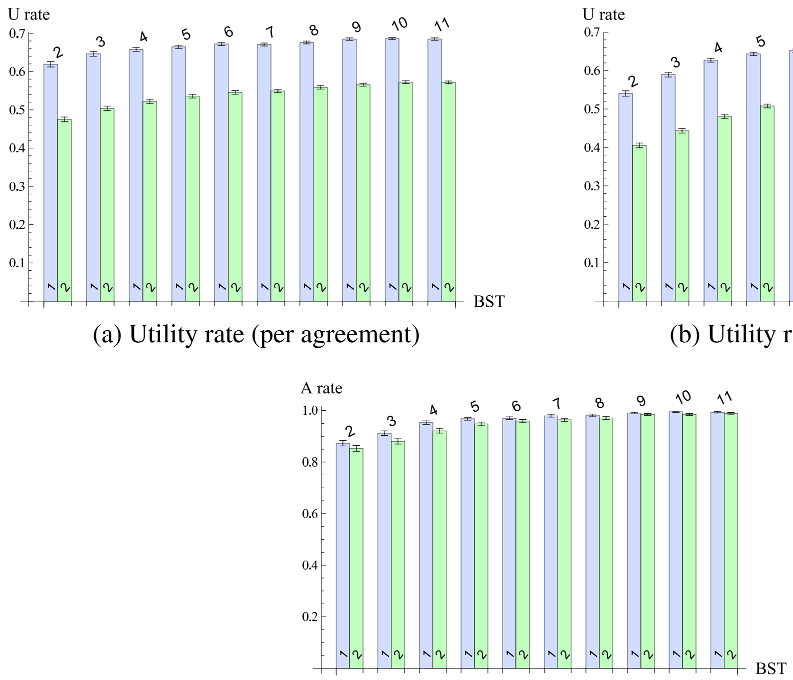
Figure 7.10: *The effect of different buyers' β values on the utility rate and the agreement rate*

The Nash product rate and the utility difference rate results are shown in Figure 7.10. Figures 7.10a and 7.10b show that the **GMMM** outperforms *GS* in terms of the Nash product rate per agreement and the Nash product rate per encounter.

When the β values becomes large, Nash product rate increases for both strategies since a conceder agent tends to offer more concessions and hence the opponents gain higher agreement utilities. The utility difference rate results are shown in Figures 7.10c and 7.10d. As before, the **GMMM** strategy produces high utility difference rates when compared to the utility difference rates produced by *GS*.

7.3.1.3 Number of the Seller Agents per Object

In this section, we investigate how the initial number of seller agents per a negotiation object can affect the negotiation results. The experimental settings are similar to the settings discussed in section 7.2.1. The two buyer agents use the same randomly selected parameters such as deadline and β since we are testing only for the number of seller agents per object. The numbers of the seller agents per object are shown on the above of the bars in Figures 7.11 and 7.12. The experiments started with 2 seller agents per objects and increased up to 11 seller agents per object.



(a) Utility rate (per agreement) (b) Utility rate (per encounter)

(c) Agreement rate

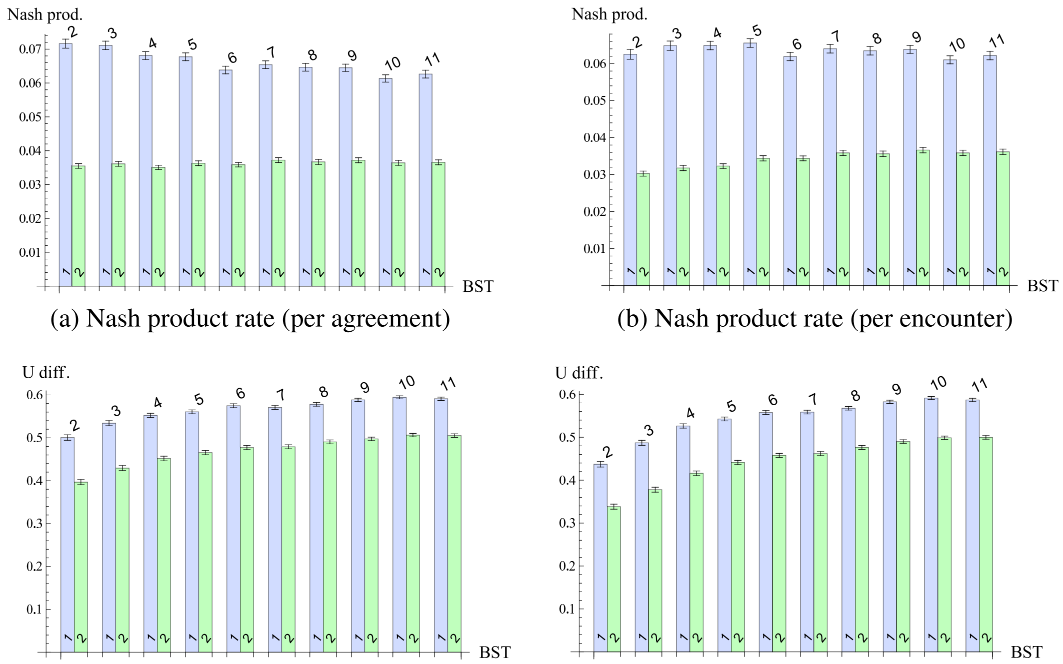
$(1 \rightarrow GMMM\ strategy, 2 \rightarrow GS)$

(*The numbers above the graph bars refer to the number of seller agents per object*)

Figure 7.11: *The effect of different number of sellers on the utility rate and the agreement rate*

Figure 7.11 shows experimental results for the utility rates and the agreement rates. When the number of the seller agents per objects increases, both strategies perform better in terms of the utility rates, see Figures 7.11a and 7.11b. However, the **GMMM** strategy outperforms *GS* in all cases. Both strategies behave similarly in terms of the agreement rates, see Figure 7.11c. However, the **GMMM** strategy performs similar or better than *GS* in terms of the agreement rate under all numbers of the seller agents per object.

It is noticed that when the number of seller agents per object is small, e.g., 2, the agreement rate is about 20% lower than when the number of the seller agents per object is greator than 4, see Figure 7.11c. Large number of seller agents per object is considered favourable to the buyer agents.



(a) Nash product rate (per agreement)

(b) Nash product rate (per encounter)

(c) Utility Difference rate (per agreement)

(d) Utility Difference rate (per encounter)

$(1 \rightarrow GMMM\ strategy, 2 \rightarrow GS)$

(*The numbers above the graph bars refer to the number of seller agents per object)*

Figure 7.12: *The effect of different number of sellers on the Nash product rate and the utility difference*

The results for the Nash product rate and the utility difference rate results are shown in

Figure 7.12. The results for the Nash product rate per agreement and the Nash product rate per encounter results are shown in Figures 7.12a and 7.12b respectively. The Nash product rates show that the **GMMM** strategy outperforms *GS* significantly in both graph results. When the number of the seller agents increases, the utility agreement of the opponents can be lower which affects the Nash product rate, see Figure 7.12a.

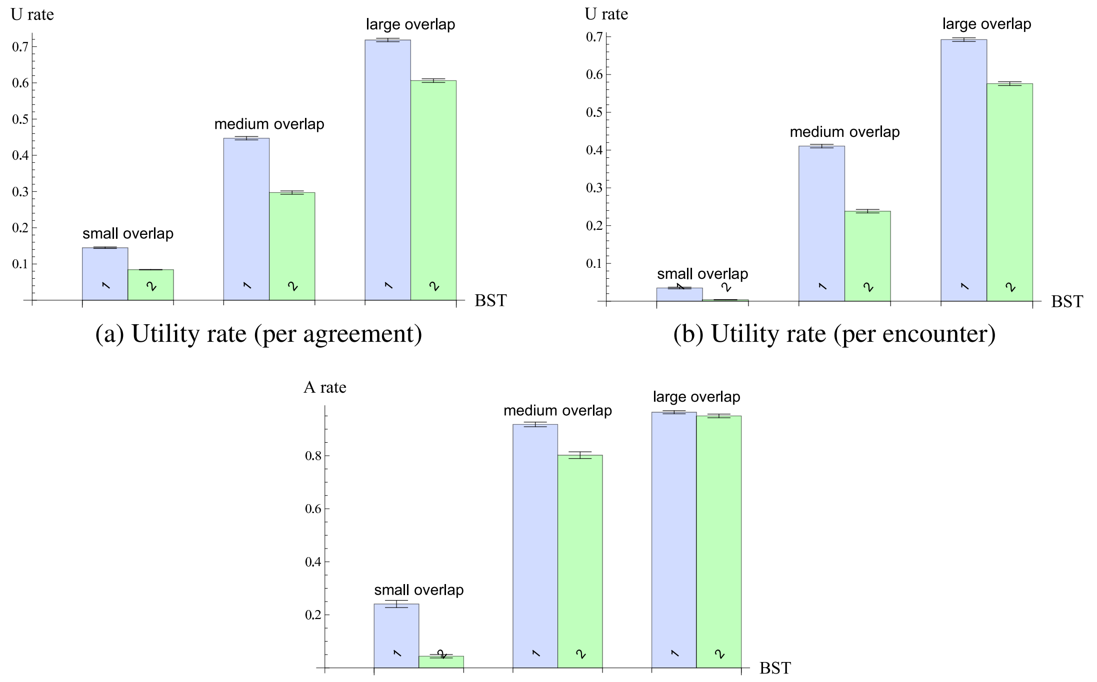
The utility difference rate results are presented in Figures 7.12c and 7.12d. The results here are consistent as before. When the number of the seller agents per object increases, both strategies tend to have larger utility rate differences. The reason is that when the number of the seller agents are large, the buyer agents benefit from this situation and gain higher utility rates than when the number of seller agents per object is smaller.

7.3.1.4 Length of the Agreement Zone

The length of the agreement zone between opponent agents can affect the negotiation outcomes. This section tests the buyers' strategies under different overlap percentages (i.e., different agreement zone lengths) between the reservation intervals of the objects' issues. For example, assume that the reservation interval for a buyer agent for price is $[5, 20]$. It means the initial offer for that agent is $5 and the maximum price (reservation value) is $20. If the opponent agent has the same reservation interval too, i.e., $[5, 20]$ where the starting offer is $20 and the minimum price (its reserve price) is $5, then the two agents have 100% overlap and the agreement zone is the longest possible. To see how the overlap percentage affect the negotiation results for the two strategies, the follwoing experimental aresults are presented and discussed. For more information about the overlap percenages, see Section 4.5.2.

Three types of overlap percentages are used in the experiments: small (5%- 25%), medium (30%- 60%) and large overlap (70%- 100%). The results indicate that when the overlap is large (i.e., the agreement zone is large), the negotaion outcome are positively affected and vice versa, see Figure 7.13 and 7.14.

Figure 7.13 presents the utility rate and the agreement rate results. The **GMMM** strategy outperforms *GS* in terms of utility rates, see Figures 7.13a and 7.13b. In addition, the **GMMM** strategy outperforms *GS* in terms of the agreement rates in case the agreement zones are small and medium, see Figures 7.13c. When the agreement zone



(a) Utility rate (per agreement)

(b) Utility rate (per encounter)

(c) Agreement rate

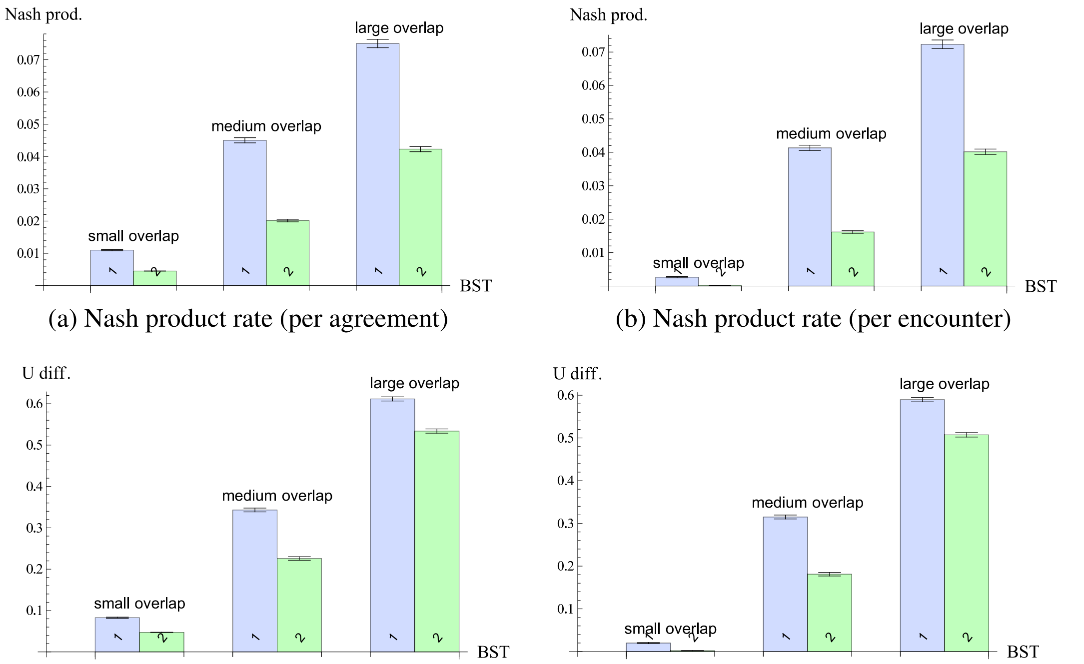
$(1 \rightarrow GMMM\ strategy, 2 \rightarrow GS)$

Figure 7.13: *The effect of different agreement zone lengths on the utility rate and the agreement rate*

is large, both strategies perform similarly.

The Nash product rate and the utility difference rate results are presented in Figure 7.14. The results here are consistent with the results presented earlier. The **GMMM** strategy outperforms *GS* in terms of the Nash product rates, see Figures 7.14a and 7.14b. As the case with the utility rates and the agreement rates, when the agreement zone gets larger, both strategies perform better. In addition, the **GMMM** strategy produces higher utility rate differences than the utility rate differences produced by *GS*, see Figures 7.14c and 7.14d.

In general, when the agreement zones between agents increase, both strategies produce better results.



(a) Nash product rate (per agreement)
(b) Nash product rate (per encounter)
(c) Utility Difference rate (per agreement)
(d) Utility Difference rate (per encounter)

$$(1 \rightarrow GMMM\ strategy, 2 \rightarrow GS)$$

Figure 7.14: *The effect of different agreement zone lengths on the Nash product rate and the utility difference rate*

7.4 Summary

This chapter investigates the coordination scenarios where the number of distinct negotiation objects is multiple and the number of negotiation issues per object is multiple too. First, a coordination mechanism is proposed for the **MMS** coordination scenario where each object has a single provider. This scenario exists in monopolistic markets where there is a single provider that controls the supply of a certain market item(s). On the other hand, a global coordination mechanism is proposed for the **MMM** coordination scenario where each object has multiple issues and multiple prospective providers.

The **MMS** coordination strategy manipulates the local reservation values for the common issues of the different objects. The seller agents' concessions on the common issues are analyzed and every common issue is assigned a possibly new reservation value accordingly. The coordination mechanism is repeated at the start of every negotiation round. The mechanism is validated empirically under different negotiation environments. It is compared with the general negotiation strategy where the negotiation variables are initialized at the start of every negotiation encounter and kept unchanged. The **MMS** and general strategies are tested under different deadline lengths and different concession curve convexities. The **MMS** strategy outperforms the general strategy significantly in terms of the utility rates, the Nash product rates and the agreement rates. The **MMS** strategy are proven to be effective and robust in the given negotiation environments. Finally, it produces higher utility difference rates than the utility difference rates produced by the general strategy.

To manage the bidding strategy for the **MMM** coordination scenario, a global coordination mechanism is proposed. The **GMMM** strategy manages the local reservation values based on the values of the last opponents' offers. The global strategy does not require an initial local reservation value matrix if the seller agents start proposing. At the start of the every negotiation round, the **GMMM** strategy constructs the local reservation value matrix from the last sets of the received offers. An initial set of experimental results are presented. The proposed strategy is tested under different deadline lengths, under different concession curve convexities, under different numbers of seller agents per object and under difference agreement zone lengths. The results show that the **GMMM** strategy outperforms the general strategy in terms of the utility rates, the Nash product rates and performs similar or better in terms of the agreement rates. As in the **MMS** strategy case, the **GMMM** strategy shows higher utility difference rates than the ones produced by the general strategy.

The **GMMM** strategy shows higher utility rates and lower Nash product rates than the ones shown by the **MMS** strategy because the **GMMM** strategy benefits from existing multiple providers per object. Finally, the proposed mechanisms are compared with the general strategy because the coordination scenario presented in this chapter is rarely investigated in the literature.

Chapter 8

Conclusion

This thesis investigates the bidding negotiation strategies in the one-to-many negotiation where a buyer agent negotiates concurrently with multiple seller agents. The main assumptions here are that the agents negotiate under incomplete knowledge where the preferences over the outcomes, the utility structure, the offer generation tactics and the deadlines are considered private information for each agent.

To classify different negotiations, the three main negotiation components and their numbers are considered: the number of negotiation objects which is equivalent to the number of the required agreements in our case, the number of negotiation issues per object and the number of providers (seller agents) per object. Accordingly, the one-to-many negotiation is classified into five different coordination scenarios, namely: **SSM, MSM, SMM, MMS, MMM**, where **S** stands for single and **M** stands for multiple. The first letter refers to the number of negotiation objects, the second letter refers to the number of issues per object and the third letter refers to the number of providers per object. For example, the **SSM** scenario indicates the situation where a buyer agent seeks to procure a single object characterized by a single issue and there are many available providers willing to provision that object. Each one-to-many coordination scenario is investigated and one or more novel dynamic bidding mechanism(s) (dynamic negotiation strategy(s)) are proposed. Since the main problem addressed in this thesis is to coordinate the bidding strategies for multiple concurrent negotiations during negotiation, i.e, real-time coordination, the proposed solution approach base its coordination decisions on the level of cooperation of the current opponents in terms of their concessions in the current negotiation. The coordination mechanisms presented in this thesis do not consider any historical information since the negotiations are assumed to be as a one-off type. Accordingly, all the proposed bidding strategies are characterized by their dynamicity that depends only on the current behaviors of the seller agents in terms of their concessions in the current negotiation. The proposed coordination mechanisms for the one-to-many negotiation consider managing the negotiation variables (e.g., convexity of the concession curve) during negotiation. The collection of the negotiation variables and their values represent the current negotiation strategy for an agent. The proposed bidding strategies are empirically validated against the state-of-the-art negotiation strategies. The next few paragraphs discuss briefly the proposed mechanism(s) for each coordination scenario.

For the **SSM** coordination scenario, where a buyer agent seeks to procure a single object (e.g., a service) characterized by a single issue (e.g., price) and many providers for that object exist, a dynamic negotiation strategy is proposed to manage the buyer agent's concession curve convexities (each buyer's delegate can have a different concession curve convexity) during negotiation. The decision making mechanism for managing the convexity curves during negotiation depend on the collective behaviors of the current opponents. In each negotiation round, the behaviors of the current seller agents are analyzed and a new convexity is assigned to each concession curve of each delegate. The proposed negotiation strategy is tested against 4 different negotiation strategies. One is a general strategy where its negotiation parameter values (e.g., concession curve convexity) are initialized at the start of negotiation and stay without any change throughout negotiation and quit negotiation as soon as it reaches an agreement. The second strategy keeps negotiating until it reaches its deadline then selects the best acceptable agreement. The last two strategies adjust either the convexity curve or the reservation value during negotiation. All strategies are tested in different negotiation environments. The experimental results show that the proposed negotiation strategy outperforms the benchmark strategies in terms of the utility rates and performs similar or better in terms of the agreement rates in most situations.

Different measures can be used to evaluate the behaviors of the current opponents during negotiation: early concessions, most recent concessions and utilities of the last offers. In addition, any combination between the measures can also be used to evaluate the behaviors of the opponents. For example, the experiments that are conducted to evaluate the proposed coordination mechanism for the **SSM** scenario evaluate the current opponents by using 50% from the utilities of the last offers measure and 50% from the most recent concessions measure. A set of experiments are designed to evaluate each measure empirically. The experimental results show that (in most cases) the recent concessions measure performs similar or better than the other evaluation criteria.

The **MSM** coordination scenario is a negotiation scenario where a buyer agent seeks to procure multiple distinct objects (e.g., multiple services) where each object has a single issue (e.g., price) and multiple providers. Three coordination mechanisms are proposed: global coordination mechanism, local coordination mechanism and hybrid coordination mechanism. The global coordination mechanism manages the local reservation value for each issue of each object during negotiation taking into consideration the behaviors of all the seller agents, i.e., global view. The local coordination mechanism manages the convexity of the concession curve for a set of delegates of a given object. In other words, in the local coordination mechanism, the behaviors of the providers of a certain object are analyzed without considering the behaviors of the providers of other objects, hence the name local. Finally, the hybrid mechanism combines both, the global mechanism and the local mechanism. To generate counteroffers in every negotiation round, the hybrid coordination mechanism receives new local reservation values from the global strategy and receives the convexity of the concession curve for each set of delegates (of a given object) from the local strategies since there would be local strategies equal to the current number of the negotiation objects. Under tough negotiation environments where the length of agreement zones between agents are small, the experimental results show that the global strategy outperforms the general strategy and a state-of-the-art negotiation strategy (that manages the local reservation values) in terms of the agreement rates and performs similar or better than the state-of-the-art strategy in terms of the utility rates. The local strategy achieves better utility rates than the benchmark strategies. The hybrid strategy outperforms all strategies, including both, the global and local strategies, in terms of both, the utility rates and the agreement rates.

Since the **SMM** coordination scenario considers a situation where a buyer agent seeks to procure an object characterized by multiple negotiation issues and the number of the providers is multiple, a meta-strategy model is proposed that alternates between a concession tactic and a trade-off tactic during negotiation. In addition, a novel iterative offer generation mechanism is proposed and used to generate counteroffers for the buyer agent. It includes two negotiation tactics, the IOG-trade-off tactic and IOG-concession tactic. Whether the buyer agent decides to use the IOG-concession tactic or the IOG-trade-off tactic, it starts offering concessions on the issues that are believed to be more important to the opponent. This way of offering concessions helps reach an agreement quickly and improves the social welfare of the system. The meta-strategy is tested against two other benchmark negotiation strategies. The first one is the general strategy (sometimes called tactic) and the second is a strategy that manages the convexity of the concession curves. Four different performance criteria are considered in the experiments: utility rate, agreement rate, Nash product rate and utility difference rate. The Nash product rate measures the social welfare while the utility difference rate assesses the fairness of an agreement. A set of experiments are designed and implemented to evaluate the meta-strategy under different negotiation environments. The experimental results show that the meta-strategy performs better than the benchmark strategies in terms of the utility rates and the Nash product rates. It also performs similar or better than the benchmark strategies in terms of the agreement rates. In most cases, the meta-strategy shows equal or higher utility difference rates than the benchmark strategies. In addition, the experiments show that all strategies perform better in terms of the utility rates, the agreement rates and the Nash product rates when the number of the seller agents per object is large. On the other hand, the opposite results (except for agreement rates) are noticed when the number of the issues per object is large. Moreover, a second set of experiments is dedicated to evaluate the IOG-concession tactic against the general strategy that is considered as a concession tactic. Under different deadlines, the IOG-concession tactic outperforms the general strategy in terms of the utility rates and the Nash product rates. Both tactics perform similar in terms of the agreement rates and the utility difference rates.

The coordination scenario **MMS** considers a monopolistic market where there is one provider for each object. The scenario considers a situation where a buyer agent seeks to procure multiple objects and each object is characterized by multiple issues and there is a single provider for each object. Since each object in the given scenario is assumed to have multiple issues, the coordination mechanisms proposed for this scenario depend on the existing of the common issues between different objects. The proposed coordination mechanism relies on the fact that different seller agents can have different preferences over different issues. For each common issue amongst two or more objects, the coordination mechanism detects for possible differences in the importance of each object's issue from each object's provider's point of view. The second step is to change the local reservation values by shifting some resources from the more lenient provider(s) to the less lenient ones, that is to help the delegate agents who are negotiating with difficult opponents to reach an agreement. This process is repeated for each issue of each object. Since this scenario is rarely considered in literature, the proposed mechanism is evaluated against the general strategy. The experimental results show that the proposed mechanism outperforms the general strategy in terms of the utility rates per encounter, the agreement rates and Nash product rates per encounter in all of the considered negotiation environments.

The last coordination scenario is the **MMM** scenario where a buyer agent is negotiating with multiple seller agents over multiple distinct objects. Each negotiation object is characterized by several issues and has multiple providers. The **MMM** scenario is the most complex one. Since there are multiple objects and each object has multiple providers, there would be two levels of coordination, as the case with the **MSM** scenario, a global coordination and a local coordination. The global coordination mechanism uses the previous received offers to construct a new local reservation values matrix in every negotiation round. The elementary experimental results show that this method outperforms the general strategy in terms of the utility rates, the agreement rates and provides better social welfare. However, more experimental work is needed to further validate the mechanism. Moreover, further work is planned to design local and hybrid coordination mechanisms.

Finally, a novel and general negotiation model that utilizes the notion of a negotiation object is proposed. A negotiation object can represent either a physical item or a nonphysical item. The model can be used to describe most negotiations including: one-to-one, one-to-many and many-to-many negotiation. The model considers three main criteria in any negotiation process: negotiation objects, negotiation issues and negotiating agents. The numbers of the opponents on each of two negotiation sides determine the form of negotiation. In the one-to-many negotiation, the number of the negotiation objects, the number of issues per object and the number of providers per object determine the type of the coordination scenario, see paragraph 2 in this section.

8.1 Answers to the Research Questions

The main research question of this thesis that is stated in Section 1.3 is:

Can the bidding strategy for multiple concurrent one-to-many negotiations be coordinated by adapting an agent's negotiation strategy parameters during negotiation?

The main research question is split into 4 different research questions, the questions and the answers are listed in the following:

1- Can the approach of adapting the **convexity of the concession curves** *during multiple concurrent negotiations be an effective method in improving one or more of the negotiation performance criteria.*

Managing the convexity of the concession curves for a buyer agent's delegates approach is proven to be an effective coordination method. Coordination methods that depend on managing the convexity of the concession curves for the delegates are proposed in the coordination scenarios **SMM** and **MSM**. The experimental results that are presented in Chapter 5 indicate that managing the convexity curves during negotiation improves the utility rates. The proposed coordination mechanism significantly outperforms the state-of-the-art coordination techniques in terms of the utility rates without significantly affecting the agreement rates. The reason is that the proposed coordination mechanism considers the collective behaviors of all the seller agents in a given negotiation round to decide the slop of the concession curves in the next negotiation round for one or a group of delegates. Managing the convexity of the concession curves are mainly used with a single continuous issue. However, the approach can still be used in the multiple issue case when the convexity of utility concession curve is considered instead of considering the concession curve of a certain issue. The convexity of the concession curves are managed in a way to propose counteroffers with different utility values in each negotiation round. The seller agent who is desperate to reach an agreement usually offer more concessions than the non-desperate one. Accordingly, the proposed coordination method proposes counteroffers with low utility values for the desperate seller agents. It does the opposite with the non-desperate seller agents. The aim of this strategy is to achieve valuable agreements (i.e., with high utility) and at the same time, it does not jeopardize reaching an agreement.

2- Can the approach of **alternating between different negotiation tactics** *during multiple concurrent negotiations be an effective approach in improving one or more of the negotiation performance criteria?*

A meta-strategy is proposed for managing the bidding strategy in the one-to-many negotiation. It is used in the **SMM** coordination scenario. The meta-strategy alternates between a concession tactic and a trade-off tactic. Before using either tactic, the seller agents are classified into two groups: favorable group and unfavorable group. The trade-off tactic is used with the favorable group while the concession tactic is used with the unfavorable group. The favorable group contains the seller agents that offer high concessions. The meta-strategy is tested empirically and the results are presented in Chapter 6. The results show that the meta-strategy significantly outperforms the benchmark strategies in terms of the utility rates, the Nash product rates and performs similarly in terms of the agreement rates in most of the negotiation environments that are used in the experiments. The meta-strategy produces higher utility difference rates than the other strategies in most cases. The alternating between different negotiation tactics approach are proved to be an effective negotiation method and provide positive results for most of the performance criteria. The meta-strategy uses the proposed iterative offer generation tactics to generate its counteroffers: the IOG-trade-off tactic and the IOG-concession tactic. Both tactics are designed to offer more concessions on the issues that are believed to be more important than the others from the seller agents' point of view. This kind of knowledge can be domain knowledge or it can be extracted from the current behaviors of the opponents or from historical data.

3- Can the approach of adapting the **local reservation values** *during multiple concurrent negotiations be an effective method in improving one or more of the negotiation performance criteria?*

Managing the local reservation values for multiple concurrent negotiations is shown to be an effective negotiation approach. Adopting the method of manipulating the local reservation values as a coordination approach in the one-to-many negotiation is based on the idea of existing common issues between different negotiation objects. The other important point that supports using this approach is that the seller agents can have different importance weights for different issues. The coordination approach that considers managing the local reservation values needs to consider the differences between the seller agents over the common issues. That helps in shifting the resources between different delegates appropriately during negotiation. The last condition for using this approach is that the number of the distinct objects should be more than one given that the objects have at least one common issue. Coordination mechanisms that are based on managing the local reservation values are used in the coordination scenarios **MSM** and **MMS** and they can also be used in the scenario **MMM** as well. For the scenario **MSM**, the coordination mechanism is called global coordination mechanism since it considers the collective behaviors of all the sets of the seller agents where each set contains the seller agents that can provide one of the negotiation objects. The experimental results presented in Chapter 5 show that the global coordination mechanism outperforms the benchmark strategies in terms of the agreement rates and performs equal or better in terms of the utility rates and in most of the used test cases when the overlap percentages between the reservation values of issues are small. In addition, the experimental results presented in Chapter 7 indicate positive performance for the proposed coordination mechanism in terms of the agreement rates and the Nash product rates without significantly affecting its performance in terms of the utility rates. The described coordination mechanisms are dynamic ones since the changes in the local reservation values are made after reaching an agreement over any object and before. The values of different objects are taken into consideration before changing any local reservation value. In addition, the delegates or group of delegates that require more resources are selected based on who needs more.

4- Can the approach of **managing negotiation strategies at both, the global level and local level** *during multiple concurrent negotiations be an effective method in improving one or more of the negotiation performance criteria?*

When the coordination scenario involves multiple objects and multiple providers for each object like the scenarios **MSM** and **MMM**, two levels of coordination can exist. The first level manages the items that are shared between all negotiation objects such as the common issues. The coordination at the global level involves managing the local reservation values for the common issues. On the other hand, the process of procuring each object is another domain of coordination since the behaviors of each set of the seller agents that provide a given object can be used to coordinate the responses of the buyer agent against that particular set of seller agents without considering the behaviors of the other sets. This is called the local coordination. The local coordination mechanism involves managing the convexity of the concession curves for the set of delegates where each set is responsible for procuring one negotiation object. The local coordination mechanism runs a number of times equal to the number of the current negotiation objects. Again, the experimental results presented in Chapter 5 show that the global coordination mechanism outperforms the benchmark strategies in terms of the agreement rates and performs equal or better in terms of the utility rates. Similar results are shown in Chapter 7 except that the results in Chapter 7 show that the global coordination mechanism outperforms the benchmark strategy in terms of Nash product rates. The results presented in Chapter 5 show that the proposed local coordination mechanism outperforms other mechanisms in terms of utility rates without significantly affecting the agreement rates. When the two coordination mechanisms are combined, a hybrid coordination mechanism is constructed. The hybrid mechanism needs two pieces of information before generating its offers at the start of every negotiation round. First, it needs the local reservation values which are taken from the global coordination mechanism. Second, it needs the convexities of the concession curves for each set of delegates which are taken from the local coordination mechanism. In the given negotiation environments, the experimental results presented in Chapter 5 show that the hybrid coordination mechanism outperforms all strategies including the global and local coordination strategies in terms of the utility rates and the agreement rates.

The answers to the above four questions are collectively the answer to the *main research question*. The proposed coordination mechanisms that are based on adapting an agent's negotiation strategy parameters during negotiation, are shown to be effective mechanisms in managing the bidding strategy of the agent, by improving one or more negotiation performance criteria.

8.2 Directions for Future Work

First of all, the work presented in Chapter 7 needs to be revisited. Given the fact that one of the coordination scenarios presented in the chapter is the most complicated one, more experimental work is needed to test the proposed coordination mechanism under more experimental settings. The effect of the number of negotiation issues per object and the number of seller agents per object need more analysis. In addition, the effect of the number of common issues needs to be studied. It is expected that if the number of common issues increases, the proposed mechanisms perform better. Moreover, more investigation for the proposed coordination mechanisms is required to study the effect of using both, the trade-off tactic at the local coordination level and the hybrid strategy.

The works in this thesis consider agents in electronic markets representing buyers and sellers. Other domains need to be investigated to study the potential of using negotiation between agents to reach a certain goal. One of the main problems of the scheduling algorithms is that they are static and depend on previous information and cannot accommodate for new changes during the execution of the assigned tasks. In the task assignment problem where agents may exchange proposals that carry certain arguments that support their claim, agents can build their task schedule on the fly without the need for any scheduling algorithms. Agents need only to be aware of the goal(s) and constraints.

One of the important negotiation parameters is deadline. The effect of changing the deadline length during negotiation is rarely considered in literature. One of the important factors that can affect managing the deadline length during negotiation is the number of opponents in the current negotiation and the expected number of opponents who may enter or leave negotiation in the future. When the number of opponents in the current negotiation is large and/or the expected number of opponents to arrive is more than the expected number of agents who may leave negotiation, the situation for the buyer agent is considered favorable and it may increase the deadline length to improve the chances of reaching a valuable agreement. On the other hand, if the number of current opponents is small and/or the number of expected opponents to arrive is less than the expected number of opponents who may leave negotiation, the situation for the buyer agent becomes unfavorable and it may need to shorten the deadline length which imply increasing the amount of concession offered in the next negotiation rounds to guarantee reaching an agreement.

Although this thesis presents the solution for the coordination problem from a buyer agent's point of view, a seller agent can still use the proposed mechanism to coordinate its actions when negotiating with multiple buyer agents. One of the possible dimensions of investigation is the seller agent's trust and reputation criteria. A seller agent may consider its reputation an important factor especially if the identity of the seller agent is easily identified or the seller agent purposely identifies its identity to help in maximizing its sales. In such situation, the seller agent needs to balance between the expected gain from executing the proposed coordination mechanisms and the trust and reputation it can gain/lose from executing those mechanisms.

The buyer's delegates presented in this thesis are centrally controlled by the buyer agent. When agents are distributed and independent, they may form coalition to strengthen their stance. Using agent coalition as a way to improve the bargaining power of a set of agents during negotiation is a potential track for future work. Agents may also exchange some information during negotiation that benefits them. An agent needs to select what information to convey, when and to whom. Exchanging relevant information between agents in a coalition can affect the offer generation process in a way that benefits all agents in the coalition.

The problem of inferring the preferences of an opponent over different issues is briefly introduced in Chapter 6. The initial idea proposed in the chapter is to use the consecutive amount of concessions offered on each issue during the course of negotiation as a method of inferring the relative preferences of the opponent over different issues. This needs to be investigated thoroughly using empirical and/or theoretical methods. Inferring the preferences of opponents over the issues of negotiation allows the proposing agent to manage its concessions on the different issues in a way that improves both, the utility of an agreement and the social welfare of the system.

Finally, a user friendly e-market system that allows users to create buyer and seller agents where the buyer/seller agents are able to select and use one of the proposed coordination mechanisms during negotiation is the target of future work.

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