Automated Statistical Forecasting for Quality Attributes of Web Services

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Abstract

Web services provide a standardized solution for service-oriented architecture. Consumers of such services expect they will meet quality of service (QoS) attributes such as performance. Monitoring such QoS attributes is necessary to ensure conformance to requirements. However, the reactive detection of past QoS violations can lead to critical problems as the violation has already occurred and consequent costs may be unavoidable. To address these problems, researchers have proposed approaches to proactively detect potential violations using time series modeling. In this thesis, these approaches are reviewed and their limitations are highlighted. One of the main challenges of effective time series forecasting of diverse Web services is that their stochastic behavior needs to be characterized before adequate time series models can be derived. Furthermore, given the continuously changing nature of service provisioning and demand, the adequacy and forecasting accuracy of the constructed time series models need to be continuously evaluated at runtime.

In this thesis, these challenges are addressed, and the outcome is a collection of QoS characteristic-specific automated forecasting approaches. Each one of these approaches is able to fit and forecast only a specific type of QoS stochastic characteristics, however, taken together they will be able to fit different dynamic behaviors of QoS attributes and forecast their future values. In particular, the thesis proposes an automated forecasting approach for nonlinearly dependent QoS attributes, two automated forecasting approaches for linearly dependent QoS attributes with volatility clustering (*i.e.* nonstationary variance over time), and two automated forecasting approaches for nonlinearly dependent QoS attributes with volatility clustering. These forecasting approaches provide the basis for a general automated forecasting approach for QoS attributes. The accuracy and performance of the proposed forecasting approaches are evaluated and compared to those of the baseline ARIMA time series models using real-world QoS datasets of Web services characterized by nonlinearity and volatility clustering. The evaluation results show that each one of the proposed forecasting approaches outperforms the baseline ARIMA models.

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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 in the text of the thesis. 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.

Ayman Ahmed Amin Abdellah

List of Publications

The following papers have been accepted and published during my candidature. The thesis is largely based on these papers.

- **Ayman Amin**, Lars Grunske, and Alan Colman, "An Approach to Software Reliability Prediction based on Time Series Modeling," *The Journal of Systems and Software*, Volume 86, Issue 7, Pages 1923–1932, 2013.

- **Ayman Amin**, Lars Grunske, and Alan Colman, "An Automated Approach to Forecasting QoS Attributes Based on Linear and Non-linear Time Series Modeling," *in proceedings of the 27th IEEE/ACM International Conference on Automated Software Engineering (ASE)*, Germany. IEEE/ACM, 2012.

- **Ayman Amin**, Alan Colman, and Lars Grunske, "An Approach to Forecasting QoS Attributes of Web Services Based on ARIMA and GARCH Models," *in proceedings of the 19th IEEE International Conference on Web Services (ICWS)*, USA. IEEE, 2012.

- Indika Meedeniya, Aldeida Aleti, Iman Avazpour and **Ayman Amin**, "Robust ArcheOpterix: Architecture Optimization of Embedded Systems Under Uncertainty," *in proceedings of the 2nd International ICSE Workshop on Software Engineering for Embedded Systems (SEES)*, Switzerland. IEEE, 2012.

- **Ayman Amin**, Alan Colman, and Lars Grunske, "Statistical Detection of QoS Violations Based on CUSUM Control Charts," *in proceedings of the 3rd ACM/SPEC International Conference on Performance Engineering (ICPE)*, USA. ACM, 2012.

- **Ayman Amin**, Alan Colman, and Lars Grunske, "Using Automated Control Charts for the Runtime Evaluation of QoS Attributes," *in proceedings of the 13th IEEE International High Assurance Systems Engineering Symposium (HASE)*, USA. IEEE, 2011.

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Abbreviations

ACF: Autocorrelation Function

ARIMA: Autoregressive Integrated Moving Average

ARMA: Autoregressive Moving Average

AV: Accuracy Value

FMV: F-measure Value

GARCH: Generalized Autoregressive Conditional Heteroscedastic

HTTP: Hypertext Transfer Protocol

MAPE: Mean Absolute Percentage Error

MAPE-K: Monitor, Analyze, Plan, Execute -Knowledge

NPV: Negative Predictive Value

PACF: Partial Autocorrelation Function

QoS: Quality of Service

SLA: Service Level Agreement

SETARMA: Self Exciting Threshold ARMA

SLO: Service Level Objective

SOAP: Simple Object Access Protocol

SV: Specificity Value

UDDI: Universal Description, Discovery, and Integration

URI: Uniform Resource Identifier

W3C: World Wide Web Consortium

WSDL: Web Services Description Language

XML: Extensible Markup Language

Chapter 1

Introduction

Web services provide a standardized solution for service-oriented architecture (SOA) applications [176]. They are increasingly becoming used in critical and non-critical applications in order to efficiently and cost-effectively achieve business objectives. For instance, online trading, online banking, and medical services are some of these applications. The increasing use and importance of Web services are due to their practical advantages [16, 75, 128]. One of these advantages is that multiple existing Web services can be composed in order to build a service-based system that can accomplish more complicated tasks than those that can be achieved by the individual Web services [39, 128]. In addition, Web services allow components from different platforms to interact with each other, which is very useful for business-to-business integration in order to overcome problems related to global business environments such as scalability, cost of deployment, flexibility, and speed of deployment [74,213].

Along with functional requirements, Web services can be characterized and distinguished by using a set of non-functional requirements. These non-functional requirements are known as quality of service (QoS) attributes such as performance, reliability, availability, and safety [80,138,188,203]. The QoS attributes play an important role in creating, publishing, selecting, and composing Web services [11,114,248]. In addition, they assist in managing the relationship between the Web service providers and clients since their numerical target values are formulated as a col-

lection of service level objectives (SLOs) [14] in a service level agreement (SLA) that is constructed as a contract between the two parties and defines their mutual obligations [70, 98]. Moreover, the QoS attributes play an important role in adapting Web services or service-based systems, which are built out of a composition of individual Web services, in response to changes in their operational environment or/and requirements specification [7, 43]. In particular, they assist in deciding adaptation needs, evaluating alternative adaptation strategies, and triggering adaptation actions [7, 114, 195]. Consequently, several approaches have been proposed for monitoring QoS attributes and detecting violations of their requirements (*e.g.* [42, 86, 154, 162]).

Existing Approaches and Limitations in a Nutshell

Several approaches have been proposed in the research literature based on monitoring techniques in order to detect violations of QoS requirements. These approaches aim to support adaptations of Web services or service-based systems (*e.g.* [37, 156, 161, 162]), SLA management (*e.g.* [25, 152, 152, 206]), or generally runtime verification of QoS attributes (*e.g.* [48, 86, 200, 201]). Because these approaches rely on monitoring techniques [216], they detect violations of QoS requirements or SLA constrains *after* they have occurred. Therefore, these approaches reactively detect violations, which can lead to critical problems. For example, SLA management cannot avoid costly compensation and repair activities resulting from violating SLOs. In addition, adaptations are triggered reactively, which might come too late and thus lead to crucial drawbacks such as late response to critical events, loss of money or transactions, and unsatisfied users [97, 149, 204].

In order to address these limitations, approaches have been proposed for *proactively detecting* potential QoS violations. These proactive approaches aim to prevent SLA violations by predicting potential SLA violations and proactively performing some preventive actions to avert the violations before they occur [204]. In addition, they aim to support proactive adaptations by detecting the need for adaptation

before QoS violations occur [178]. Generally, these approaches for proactive detection of potential QoS violations can be grouped into three categories; online testing based approaches, machine learning based approaches, and time series modeling based approaches.

Online testing based approaches (*e.g.* [97, 150, 202]) exploit online testing techniques to detect QoS violations before they occur. Simply, an online test can detect a violation if a faulty Web service instance is invoked during the test time, which points to a potential violation the service-based system might face in its future operation when invoking this faulty instance [147]. However, these approaches rely on underlying assumptions, such as each failure of a constituent Web service of a service-based system leads to a requirement violation of that service-based system [149], which might be hard to be typically hold for real applications. Moreover, shortcomings related to online testing might limit the practical applicability of these approaches. These shortcomings include the fact that online testing can provide only general statements about Web services but not about their current execution traces [27, 163]. Testing might also require additional costs for invoking external Web services [149]. In contrast, monitoring approaches do not suffer from these shortcomings.

Machine learning based approaches (*e.g.* [118, 119, 120]) use machine learning techniques [96] to construct prediction models in order to proactively detect potential violations of QoS requirements. These approaches leverage machine learning capabilities to train prediction models using previously monitored historical QoS data. However, their limitation is that the effectiveness of machine learning models strongly relies on the historical QoS data required as a training dataset, which has to be several hundreds, or in some cases, even thousands of QoS data points in order to ensure the expected accuracy of prediction. Accordingly, applicability of these approaches is limited if only a small amount of historical data is available [204]. Moreover, the prediction models have to be re-trained after each adaptation, which is a time-consuming and computationally intensive process [165].

Several approaches (*e.g.* [73, 80, 218, 252]) have been proposed based on time series modeling for proactive detection of potential QoS violations. Generally, the idea of time series modeling [33] is to fit the collected historical QoS data in order to forecast their future values and potential violations of their requirements. The advantages of time series modeling are: (1) It is data-oriented and does not impose any restrictive assumptions on the environment of the Web service or service-based system in contrast to online testing techniques; and (2) Because its methodology is based on standard statistics theory and probability distributions, prediction models can be straightforwardly implemented without consuming much time in learning in contrast to machine learning models. However, the existing applications of time series modeling for QoS forecasting are immature and still in the initial stage, and they have some critical limitations that include: (1) Stochastic characteristics of QoS attributes have not been studied or evaluated based on real QoS data, which is required to select and use an appropriate time series model for fitting and forecasting QoS attributes; (2) Only linear time series models, especially ARIMA (Autoregressive Integrated Moving Average) models [33], are used without checking for their underlying assumptions or evaluating their adequacy; (3) There is no description of how those linear time series models can be constructed at runtime; and (4) There is no discussion of how the constructed time series models can be continuously updated and evaluated at runtime to guarantee accurate QoS forecasting.

Research Problem

Addressing the limitations of proactive approaches is required to guarantee accurate and timely forecasting for QoS attributes in order to avoid violating SLA constraints, missing proactive adaptation opportunities, and executing unnecessary proactive adaptations. Obviously, missing a proactive adaptation opportunity due to inaccurate QoS forecasting can lead to the same shortcomings as faced in the setting of reactive adaptations, which eventually would diminish the benefits of proactive adaptation [147]. Moreover, unnecessary adaptations can lead to critical short-

comings such as follow-up failures and increased costs [148, 149]. Because of the aforementioned advantages of time series modeling, this research work focuses on developing a general automated statistical forecasting approach based on time series modeling for QoS attributes. As a motivation for this work, this forecasting approach can be used to effectively support SLA and adaptation management in deciding proactive actions as well as support proactive service selection and composition. Achieving this research goal requires addressing a set of identified challenges that will be considered as contributions of this thesis.

The first challenge that needs to be addressed in this research work is evaluating the key stochastic characteristics of QoS attributes. This evaluation is an essential requirement for realizing an efficient and accurate forecasting approach that fits the QoS attributes and forecasts their future values because statistically the accuracy of the proposed forecasting approach is based on the evaluated QoS stochastic characteristics. Based on the time series modeling literature (*e.g.* [33, 184]), the QoS stochastic characteristics that need to be evaluated include probability distribution, serial dependency, stationarity, and nonlinearity.

Specifying the class of adequate time series models that can be used to fit and forecast QoS attributes is considered the second challenge. This is because of the plethora of time series modeling techniques proposed in the literature. In addition, the class of adequate time series models cannot be decided a priori but should be based on the evaluated stochastic characteristics of the given QoS attributes.

Once the class of adequate time series models is specified, the next challenge that needs to be addressed is how these time series models can be automatically constructed for the given QoS attributes. In the time series modeling literature, the construction of time series models is an iterative and human-centric process [33], however, forecasting QoS attributes needs to be achieved at runtime in an automated and continuous manner. Therefore, it is necessarily required to propose an effective automated procedure for automatically constructing the time series models without human intervention.

The last challenge that needs to be addressed is how the adequacy and forecasting accuracy of the constructed time series model can be continuously evaluated at runtime. Obviously, the stochastic characteristics of the given QoS attributes change over time depending on various uncontrolled factors [22, 192]. This implies that the adequacy and forecasting accuracy of the constructed time series model need to be continuously evaluated at runtime in order to guarantee adequate time series model that gives accurate QoS forecasting.

Overview of Research Method

The main goal of this research is to develop a general automated statistical forecasting approach based on time series modeling that will be able to adequately fit the dynamic behavior of QoS attributes and accurately forecast their future values and potential violations. In order to achieve this goal, the aforementioned challenges are formulated into research questions, and solutions are proposed to each one of them leading eventually to an overall solution.

First, in order to evaluate the stochastic characteristics of QoS attributes, real-world Web services are invoked for long time and QoS datasets are computed. Then, appropriate statistical methods/tests are applied to these collected QoS datasets in order to evaluate the probability distribution, serial dependency, stationarity (in the mean and in the variance), and nonlinearity.

Second, in order to specify the class of adequate time series models, the evaluated QoS stochastic characteristics are classified into two groups. One is related to the underlying assumptions of time series modeling which are probability distribution, serial dependency, and stationarity (in the mean). The other group specifies the class of adequate time series models which are stationarity (in the variance) and nonlinearity. Accordingly, four types of the stochastic characteristics of QoS attributes are identified and for each type the class of adequate time series models is specified.

Third, based on the well-established Box-Jenkins methodology and using effec-

tive statistical methods/tests, an automated procedure is proposed for automatically constructing time series models. Briefly, the proposed procedure identifies and estimates automatically a set of time series models that can be used to fit the QoS data under analysis. Then, it evaluates the estimated models and selects the best one based on an information criterion. Therefore, the proposed procedure solves the iterativeness and human intervention issues, which inherently exist in the Box-Jenkins methodology, in order to automatically construct the adequate time series model for the given QoS data.

Fourth, statistical control charts and accuracy measures are introduced to continuously evaluate the adequacy and accuracy of the constructed time series model, respectively. Once the control chart signals that the used time series model is not adequate any more for the underlying QoS data or the forecasting accuracy is very low based on the accuracy measure value, it becomes necessary to re-identify and re-construct other adequate time series models in order to guarantee continuously accurate QoS forecasting.

The outcome of addressing these challenges is a collection of QoS characteristic-specific forecasting approaches that together provide the basis for a general automated forecasting approach that will be able to fit different dynamic behaviors of QoS attributes and forecast their future values. QoS characteristic-specific forecasting approaches mean that each one of these approaches is able to fit and forecast only a specific type of the stochastic characteristics of QoS attributes. For example, one approach will be suitable for fitting and forecasting nonlinearly dependent QoS attributes, while another will be best suited for fitting and forecasting linearly dependent QoS attributes with nonstationary variance over time.

Various accuracy and performance aspects of the proposed forecasting approaches are evaluated and compared to those of the baseline ARIMA models. In general, this evaluation is achieved by first applying the proposed forecasting approaches and the baseline ARIMA models to the collected real-world QoS datasets. Then, accuracy metrics and the time required to construct and use the

time series model (as a measure for the performance) are computed. The results are then analyzed.

Scope of the Research

This research project proposes an automated statistical forecasting approach for QoS attributes of Web services. However, the extent of the work is restricted to a scope suitable for a PhD thesis. With regard to the QoS attributes, only two observable QoS attributes, namely response time and time between failures, are considered in this work. The current research contributions are limited to those two qualities. In addition, the research project collects the QoS datasets at runtime from the client-side assuming that the Web services are black-box and there is no access to their actual implementation.

The current research contributions can be related to the MAPE-K (Monitor, Analyze, Plan, Execute -Knowledge) autonomic control loop, which is a general conceptual framework for runtime management [104]. The MAPE-K framework consists of four components: monitoring, analysis, planning, and execution of actions. Accordingly, this thesis can be considered as a contribution limited to the MAPE-K analysis component that analyzes the QoS data along with the goals stated in terms of QoS requirements and SLA contacts.

Contributions

This thesis addresses the problem of forecasting QoS attributes by proposing QoS characteristic-specific forecasting approaches based on time series modeling that construct together a general automated forecasting approach that will be able to fit different dynamic behaviors of QoS attributes and forecast their future values. Accordingly, the research work in this thesis contains the following novel contributions.

- Sophisticated evaluation of stochastic characteristics of response time and time between failures QoS attributes is introduced based on QoS datasets from several real-world Web services belonging to different applications and domains. These

QoS stochastic characteristics include probability distribution, serial dependency, stationarity (in the mean and in the variance), and nonlinearity. The evaluation results report that the non-stationarity in the variance (*i.e.* volatility clustering) and nonlinearity are two important characteristics which have to be considered while proposing QoS forecasting approaches.

- An automated statistical forecasting approach for nonlinearly dependent QoS attributes is proposed based on SETARMA (Self Exciting Threshold ARMA [228]) time series models. This forecasting approach is shown to more effectively capture the nonlinear dynamic behavior of QoS attributes and more accurately forecast their future values and potential violations than the baseline ARIMA model.
- Two automated statistical forecasting approaches for linearly dependent QoS attributes with volatility clustering are proposed. The first forecasting approach is based on ARIMA and GARCH (Generalized Autoregressive Conditional Heteroscedastic [28]) time series models, while the second one is based on wavelet analysis [140], ARIMA and GARCH time series models. The evaluation results show that these two forecasting approaches outperform the baseline ARIMA model in forecasting linearly dependent QoS attributes with volatility clustering, and they are not equivalent in terms of accuracy and performance.
- Two automated statistical forecasting approaches for nonlinearly dependent QoS attributes with volatility clustering are proposed. The first forecasting approach is based on SETARMA and GARCH time series models, while the second one is based on wavelet analysis in addition to SETARMA and GARCH time series models. The evaluation results highlight that these two forecasting approaches outperform the baseline ARIMA model in forecasting nonlinearly dependent QoS attributes with volatility clustering. However, based on the results, these two forecasting approaches are highly different in terms of forecasting accuracy and performance.

Thesis Outline

The high-level structure of the thesis is depicted in Figure 1.1.

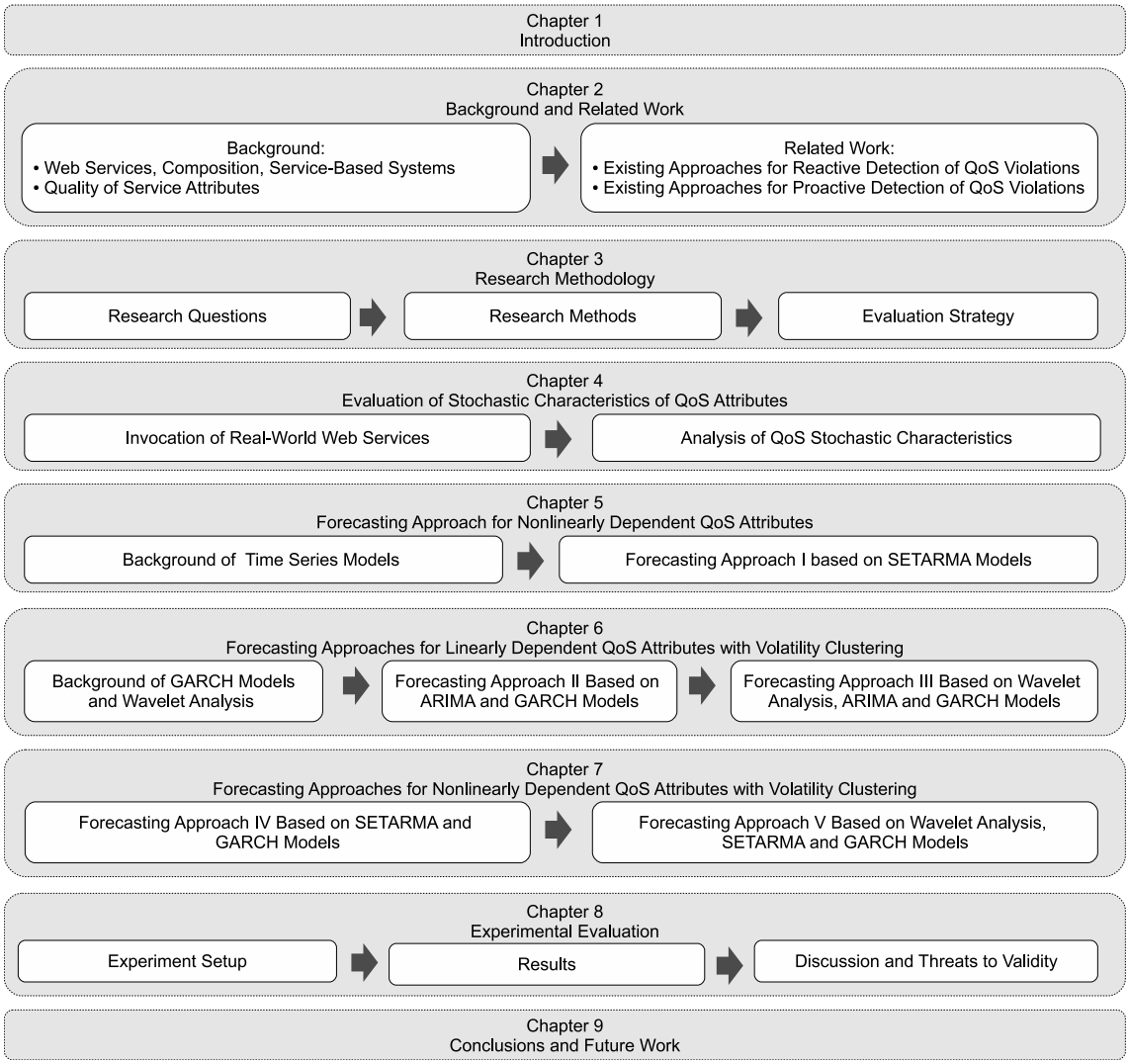


Figure 1.1: Thesis outline

Chapter 2 presents a background and a preliminary review of related work which establish a foundation for the contents presented in the remainder of the thesis. It starts with the background that includes a brief introduction to Web services, service-based systems, and QoS attributes. The second part of this chapter presents a review of the existing approaches for detecting violations of QoS requirements and discusses their limitations that are intended to be addressed in this work.

Chapter 3 formulates the research questions addressed in the thesis followed by

a description of the research method taken by this research. Chapter 3 concludes with the evaluation strategy that explains how the contributions are evaluated.

Chapter 4 explains how the real-world Web services are invoked in order to compute QoS datasets. The Chapter then presents in detail the evaluation of the key stochastic characteristics of QoS attributes, especially response time and time between failures.

Chapter 5 first introduces the background of time series models, and then presents an automated forecasting approach based on SETARMA models for nonlinearly dependent QoS attributes. Similarly, Chapter 6 first introduces the background of wavelet analysis and GARCH models, and then presents two automated forecasting approaches for linearly dependent QoS attributes with volatility clusters. The first forecasting approach is based on only ARIMA and GARCH models, while the second one is based on wavelet analysis, ARIMA and GARCH models. Chapter 7 also presents two automated forecasting approaches for nonlinearly dependent QoS attributes with volatility clusters. The first forecasting approach is based on SETARMA and GARCH models whereas the second one is based on wavelet analysis, SETARMA and GARCH models.

Chapter 8 introduces the evaluation of the accuracy and performance aspects of the proposed forecasting approaches, starting with the experiment setup followed by a detailed discussion of results. Finally, the chapter presents a general discussion followed by threats to validity of the contributions. Chapter 9 concludes the thesis and presents possible directions for future work.

Chapter 2

Background and Related Work

This chapter presents background information as well as a preliminary review of related work establishing a foundation for the contents presented in the rest of the thesis. The chapter is organized into two distinct parts. The first part of the chapter presents the background of the thesis work, which begins by presenting a brief introduction to Web services, compositions, and service-based systems. It then describes different aspects related to QoS attributes and their importance for Web services and service-based systems. The second part of the chapter presents a review of the existing approaches for detecting violations of QoS requirements and discusses their limitations in order to identify the main challenges that are intended to be addressed in this research work.

2.1 Background

Software systems are traditionally designed to operate in a well-known and stable environment, and its development and maintenance are managed by a single coordinating authority which has the responsibility for the overall quality of the resulting application. Therefore, changing the deployed software system in order to improve a prospective quality or to meet new requirements has to be through a maintenance life cycle which includes design, development, and deployment of a new version of the

software system. This traditional approach can lead to costly maintenance activities and an unsatisfactory time-to-market [70].

In the last fifteen years, the rapid development of the Internet, Web-based protocols, and open computing environments have shifted software system design and development from this scenario of closed environment to the *open world setting*, where software systems are built out of loosely coupled application components [20, 70]. A common form of such composable components are *Web services* which promote interoperation through self-describing standards-based interface. Web services are software systems that are developed, deployed, and operated by independent providers who publish them across the Internet to be used by potential clients [70]. The relationship between a Web service provider and a client can be regulated by a *service level agreement* (SLA), which is a contract between the two parties. SLA defines the obligations of each of them and particularly specifies the quality of service (QoS) level that the provider promises to guarantee and ensure [70, 98]. This scenario is referred to as *service-oriented computing* (SOC) [176]. In the rest of this section we introduce in some detail the theoretical background of the Web services and the composition process for building service-based systems. We then describe different aspects related to QoS attributes, including QoS definition and classification, monitoring approaches for QoS attributes, and the importance of using QoS attributes for Web services and service-based systems.

2.1.1 Web Services, Composition, and Service-Based Systems

The World Wide Web Consortium (W3C)[1] defines formally a Web service as "a software system designed to support interoperable machine-to-machine interaction over a network. It has an interface described in a machine-processable format (specifically WSDL). Other systems interact with the Web service in a manner prescribed by its description using SOAP messages, typically conveyed using HTTP with an XML

[1] http://www.w3.org/

serialization in conjunction with other Web-related standards" [240]. Web services are encapsulated, loosely coupled contracted software applications that can be published, located, and invoked across the Internet using a set of XML-based standards such as the SOAP [239] for messaging-based communication, the WSDL [241] for Web service interface descriptions, and the UDDI [170] for Web service registries. Thus, Web services can be characterized by three features that are "encapsulated", which means their implementation are never seen from the outside, "loosely coupled", which means changing their implementation does not require change of the invoking function, and "contracted", which means there are publicly available descriptions of their behavior, how to bind to them as well as their input and output parameters [82]. Illustrative examples include Web services that get stock price information, obtain weather reports, and make flight reservations.

A single Web service often performs a limited function within a larger business process. It therefore becomes necessary to compose multiple existing Web services to generate more complex functionality in order to accomplish more complicated tasks [39,40,128,247]. For example, there is no single Web service that can accomplish all the requirements of the travel agency, therefore the travel agency system [89,229,254] is a composition of multiple Web services of airlines, hotels and credit cards, as depicted in Figure 2.1.

The process of building service-based systems by composing existing Web services is known as a *Web service composition*, which can be seen as a construction of business process to attain a certain goal [110, 193, 236, 237]. There are two different viewpoints of the Web service composition, which are *orchestration* [55,117,135,179] and *choreography* [193, 243, 258]. These two viewpoints represent different design choices for building service-based systems. Orchestration of Web services views their invocation from a single process standpoint, while the choreographic view is a global view of interactions between Web services. While choreographic approaches and standards have not been widely adopted by industry, the use of orchestration of service workflows has become widespread. In particular, the orchestration of Web

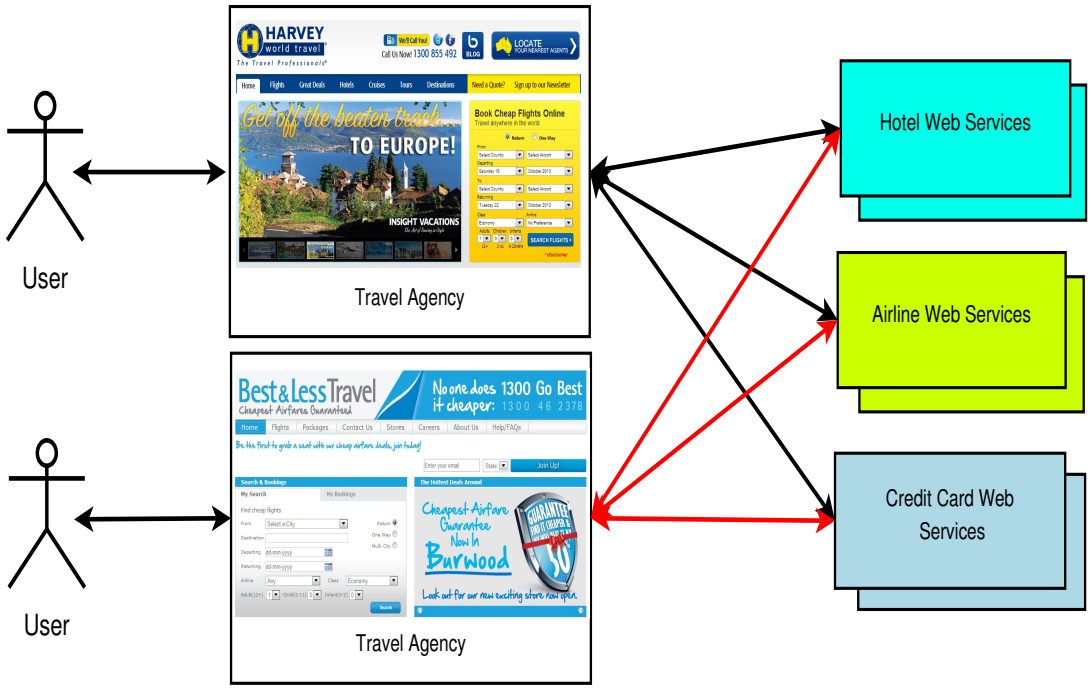


Figure 2.1: Examples of travel agency systems

services describes the sequence of Web services according to a predefined schema and run through "orchestration scripts", which are represented by business processes that can interact with both internal and external Web services [135, 179]. The orchestration always represents control from the perspective of one of the business parties, and the interactions between Web services occur at the message level in terms of message exchanges and execution order [55, 179]. WS-BPEL (Web Service Business Process Execution Language) [117, 169] is the well-established standard orchestration language that provides an XML-based grammar for describing the control logic required to coordinate Web services participating in a composition process [179, 193].

2.1.2 Quality of Service Attributes

A Web service is built to offer a specified functionality that is transparently called by a software application on another server via Internet-based protocols. The international quality standard ISO 9126 defines the term *functionality* as "the capability

of the software product to provide functions which meet stated and implied needs when the software is used under specified conditions" [106]. On the other hand, Web services are characterized and distinguished by other aspects such as performance, reliability or safety, which are called *non-functional requirements* or *quality of service (QoS) attributes*. Currently, many QoS attributes are introduced and considered in the literature. These play an important role in creating, publishing, selecting, and composing Web services. These QoS attributes are measured in terms of some metrics, for example performance can be measured in terms of response time. As a consequence, because the WSDL can describe only the functional specification of Web services, other standards such as WS-Policy [31], WSLA [112, 133], and WS-Agreement [54] have been introduced in order to describe the QoS attributes of Web services. In addition, some monitoring approaches have been proposed for collecting QoS data in order to enable the calculation of QoS metrics. In order to introduce a brief overview for these aspects of QoS attributes, in the rest of this section, a definition and classification of QoS attributes are introduced along with a listing of the important QoS attributes. Then, the monitoring approaches for collecting QoS data are summarized. Finally, the importance of using QoS attributes in Web services and service-based systems is discussed.

2.1.2.1 QoS Attributes Definition and Classification

Kritikos and Plexousakis [114] define the QoS attributes of Web services as "a set of nonfunctional attributes of the entities used in the path from the Web service to the client that bear on the Web service's ability to satisfy stated or implied needs in an end-to-end fashion".

The QoS attributes of Web services can be classified from different perspectives such as perspectives of domain, measurement, and how QoS values are obtained [98, 112, 249]. In particular, from the perspective of how QoS values are obtained, QoS attributes are classified as [98]:

- *Provider-advertised* attributes: Those attributes that are provided by the Web

services providers, which are therefore subjective to a providers' estimation such as "price or cost" of the Web service.

- *Consumer-rated* attributes: Those attributes that are computed based on the Web services consumers' feedback and evaluation such as "reputation" of the Web service.

- *Observable* attributes: Those attributes that are observed and computed based on monitoring operational events of the Web service. Indeed, majority of the QoS attributes are measured using observable metrics such as performance, reliability, availability, and safety [249]. An important characteristic of the observable QoS attributes is that they are stochastic in nature, and therefore they might be interpreted in a probabilistic sense using probability distributions rather than strictly deterministic values [253]. This is because the nature of those QoS attributes depends on unavoidable and imprecise factors of the Web services and their context [145, 192].

Researchers have introduced and discussed many QoS attributes as important aspects to the Web services [114, 141, 187, 222, 242]. These QoS attributes include performance, reliability, availability, accessibility, safety, integrity, and security. In the following, the observable QoS attributes related to the current research work are summarized with a discussion of their metrics:

- *Performance*: The QoS attribute that characterizes how well a Web service performs, which can be measured in terms of many metrics such as response time, throughput, latency, execution time, and transaction time [114, 187]. Response time is a required time to complete a Web service request, while throughput is a number of completed Web service requests at a given time period. Latency is a round-trip delay between sending a request and receiving a response, and execution time is a time taken by a Web service to process its sequence of activities [242]. Finally, transaction time is a required time for a Web service to complete one transaction, which obviously depends on

the definition of Web service transaction. Accordingly, the sum of latency and execution time gives the response time. In general, faster response time, higher throughput, lower latency, lower execution time, and faster transaction time represent good performance of a Web service [242].

- *Reliability*: Web services should be provided with high reliability which is the QoS attribute that represents the ability of a Web service to perform its required functions under stated conditions for a specified time period [114, 242]. Indeed, the reliability is the overall measure of a Web service to maintain its quality, and it is related to the number of failures per day, week, month, or year [242]. In another sense, reliability is related to the assured and ordered delivery of messages being sent and received by Web service requesters and providers [114, 222, 242]. It is usually measured by mean time between failures (MTBF) metric or the probability that a Web service request has been correctly responded with a valid response within a specified time period [116].

- *Availability*: Measures whether a Web service is present or ready for immediate consumption. Availability represents the probability that a Web service is available (i.e. up and running) [187, 194, 248]. Larger values indicate that the Web service is almost always ready to use, while smaller values indicate unpredictability as to whether the Web service will be available when it is invoked at a particular time [141]. The availability can be measured as [88,114]:

$$Availability = \frac{< upTime >}{< totalTime >} = \frac{< upTime >}{(< upTime > + < downTime >)}, \quad (2.1)$$

where $< upTime >$ is the total time that a Web service has been up during the measurement period, while $< downTime >$ is the total time that a Web service has been down during the measurement period. $< totalTime >$ is the sum of $< upTime >$ and $< upTime >$, which represents the total measurement time. It is worth mentioning that time-to-repair (TTR), which represents the time it takes to repair a Web service that has failed, is associated with availability

[222, 242]. This implies that availability is related to the reliability attribute [21, 191, 246]. Kritikos and Plexousakis [114] introduce a new attribute related to availability which is called *continuous availability*. Continuous availability represents the probability that a client can access a Web service an infinite number of times during a particular time period [114]. Indeed, continuous availability is different from availability in that it requires subsequent use of a Web service to succeed for a limited time period [114].

- *Accessibility*: Characterizes the case where a Web service is available but not accessible to some users due to external problems such as high volume of requests or network connection problems [114, 130]. Thus, accessibility is the quality aspect that represents the degree that a Web service is capable of serving a client's requests [222, 242]; and it may be expressed as a probability measure denoting the success rate or the chance of a successful Web service instantiation at a point in time [141]. Accordingly, Artaiam and Senivongse [14] propose a metric for measuring accessibility as follows:

$$Accessibility = \frac{< totalRequests >}{< totalTime >}, \tag{2.2}$$

where $< totalRequests >$ is the total number of requests for which a Web service has successfully delivered valid responses within an expected time frame, and $< totalTime >$ is the total measurement time. Researchers [141, 222, 242] point out that high accessibility of Web services can be achieved by building highly scalable systems, where scalability refers to the ability to consistently serve the requests despite variations in the volume of requests [141]. It is worth noting that either non-accessibility or non-availability constitute a "failure" from the client's point of view.

2.1.2.2 Monitoring Approaches for QoS Attributes

Once a set of QoS attributes has been defined and established for the Web service, a monitoring approach can be applied to observe the Web service during its current execution with the aim of collecting detailed data to compute the predefined QoS metrics. Many monitoring approaches have been proposed in the literature (*e.g.* [155, 168, 187, 194]). These monitoring approaches might be:

- *Passive or active* monitoring: Passive or execution monitoring is a real time approach that observes a Web service while it passes [187, 208]. On the other hand, active monitoring is performed when it is required to simulate the Web service requesters behavior [219]. Mostly, active monitoring is associated with the online testing of the Web service [147]. Researchers [5, 80, 177] discuss that passive and active monitoring approaches are complementary to each other and they can be used in conjunction with one another.

- *Continuous or adaptive* monitoring: A Web service might be monitored continuously or intermittently depending on its application and QoS requirements [80]. Thus, continuous monitoring is continually collecting and processing data about Web service's runtime behavior and usage; while adaptive monitoring observes a few selected features, and in the case of finding an anomaly it aims at collecting more data [198]. Actually, the decision of continuous or adaptive monitoring requires a trade-off between the cost and overhead of the monitoring and the timely detection of QoS violations [66, 168].

- *Internal or external* monitoring: Monitoring might be performed by Web service providers (i.e. internal or server-side monitoring [155]) or by Web service requesters (i.e. external or client-side monitoring [194]). Researchers [153, 235, 253] report that server-side monitoring is usually accurate but requires access to the actual Web service implementation which is not always possible in practice. On the other hand, client-side monitoring is independent of the Web service implementation. However, the measured values are affected

by uncontrolled factors such as networking performance, and they might not always be up-to-date since client-side monitoring is usually achieved by sending probe requests [153]. This is why some researchers [80,153] propose combining the advantages of both server-side and client-side approaches.

2.1.2.3 Importance of Using QoS Attributes in Web Services

QoS attributes play a significant role in the activities of the Web service life cycle. In the very beginning of these activities, QoS attributes allow the Web service providers to design the Web service more efficiently according to predefined QoS metrics. Therefore, the providers know the QoS level that the Web service will exhibit before making it available to its customers [114]. In addition, the Web service is constructed in such a way that it is able to provide the required functionalities and fulfil the QoS requirements. Moreover, in the testing activity, the Web service is checked to see whether it meets its QoS requirements in addition to functionalities.

QoS attributes are an important factor in the selection of Web services [11]. Particularly, if there are functionally equivalent Web services available, the customers can select the Web services based on their functionality as well as their QoS level. Consequently, there are many QoS-based selection approaches (*e.g.* [10,11,12,13,29]) introduced in literature that propose using QoS requirements to support selecting the best Web service that fulfils customer expectations.

QoS attributes can assist in managing the relationship between the Web service providers and clients. Once the clients select the Web service that they intend to use, the SLA is constructed as a contract between the clients and providers. Numerical target values of the QoS attributes, *i.e.* QoS requirements, play an important role in this SLA since they are formulated as a collection of service level objectives (SLOs) [14]. Therefore, for the Web service providers it is important to fulfil these SLOs and minimize SLA violations in order to avoid paying costly penalties or breaking the SLA contract [9, 186, 217]

QoS attributes of individual Web services are one of the main factors that has

to be taken into account in a Web service composition in order to meet the end-to-end QoS requirements of the constructed service-based systems [248]. In order to achieve the Web service composition along with optimizing the end-to-end QoS level, many QoS-aware Web service composition approaches have been proposed (*e.g.* [26, 41, 44, 45, 64]). Indeed, these approaches determine the end-to-end QoS of a composition by aggregating the QoS of the individual Web services and verifying whether they satisfy the QoS requirements for the whole composition [107, 108]. Therefore, these approaches leverage the structure of a composition that maximizes the end-to-end QoS level and fulfils the QoS constraints and preferences [248].

Finally, QoS attributes assist in managing the service-based systems. In practical applications, service-based systems are realized by composing multiple Web services which are under the control of third-parties, and thus they operate in highly dynamic and distributed contexts. Therefore, they need to be able to adapt in response to changes in their context or their constituent Web services, as well as to compensate for violations in QoS requirements [7, 43, 97, 195]. The research community has developed some approaches to achieve such adaptation which mainly depend on using QoS attributes (*e.g.* [50, 144, 153, 156, 224]). In particular, these adaptation approaches rely on the MAPE-K (Monitor, Analyze, Plan, Execute -Knowledge) autonomic control loop, which is a general conceptual framework for runtime management [104].

As depicted in Figure 2.2, the MAPE-K framework consists of four components - monitoring, analysis, planning, and execution of actions - which are responsible for maintaining the service-based system functionality as well as the QoS requirements based on adaptation capabilities. The monitoring component monitors the service-based system status and collects monitoring QoS data from different Web services. The monitoring component can achieve this activity by exploiting various proposed monitoring approaches which are discussed above in the previous subsection. The analysis component analyzes the monitored QoS data along with the goals stated in terms of QoS requirements and SLA contacts, and checks for violations of these

requirements and contracts. Whenever a QoS requirement is violated, the planning component uses a strategy to create an adaptation plan as a sequence of actions. Finally, the execution component enforces the planned actions to bring the system back to the acceptable state.

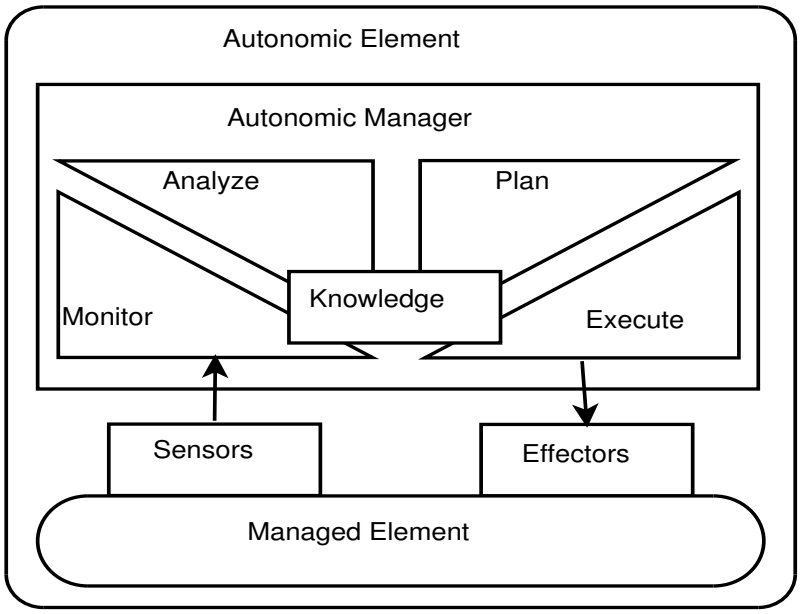


Figure 2.2: MAPE-K (Monitor, Analyze, Plan, Execute -Knowledge) autonomic control loop (Cf. [104])

2.2 Review of Related Work

Several approaches have been proposed for detecting violations of QoS requirements as a critical capability for the management of Web services or service based systems. As depicted in Figure 2.3, these approaches can be classified into two types; reactive approaches and proactive approaches. The reactive approaches detect QoS violations that have already occurred. These approaches can be classified into two groups: threshold based approaches and statistical based approaches. On the other hand, the proactive approaches are proposed to proactively detect potential QoS violations before occurring. They can be classified into three groups: online testing based approaches, machine learning based approaches, and time series modeling based

approaches.

This section begins with a review of the existing reactive approaches for detecting QoS violations and discusses their limitations. It then reviews the existing approaches for proactive detection of QoS violations and analyzes their limitations.

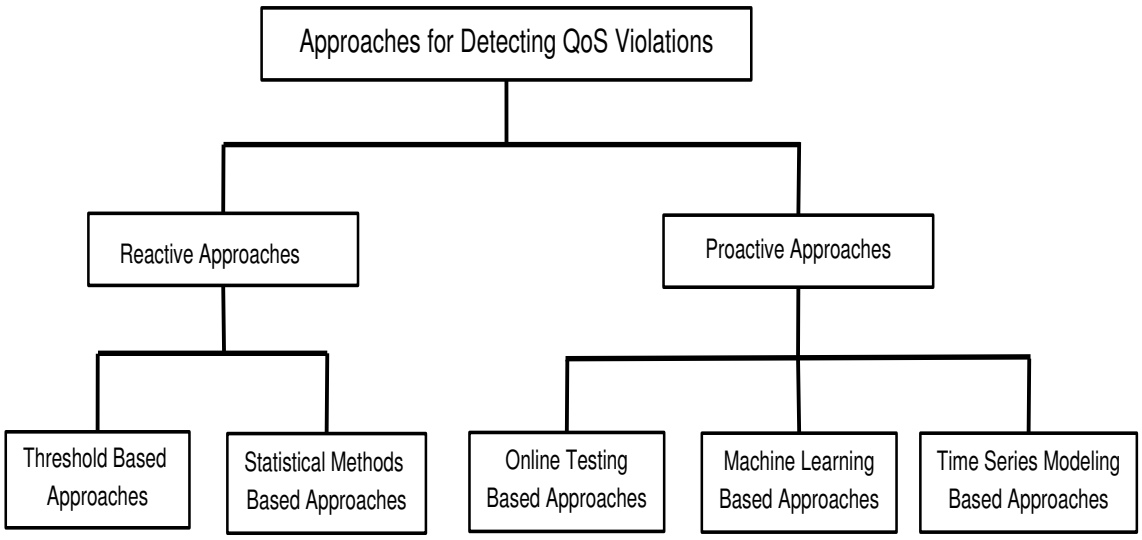


Figure 2.3: Classification of the existing approaches for detecting QoS violations

2.2.1 Existing Approaches for Reactive Detection of QoS Violations

There are many existing approaches for reactive detection of QoS violations that are proposed in different application domains, including SLA management, adaptations of Web services or service-based systems, and runtime verification of QoS attributes. These approaches can be classified into two categories: (1) Threshold based approaches, and (2) Statistical methods based approaches. In the following, these approaches are reviewed and their limitations are discussed.

2.2.1.1 Threshold Based Approaches

Several approaches have been proposed to monitor QoS attributes at runtime with the goal of detecting QoS violations in order to trigger adaptations, or to verify

whether QoS values meet the desired level to detect violations of SLOs. These approaches detect violations of QoS requirements by observing the running system and computing QoS values. If these computed QoS values exceed a predefined threshold, they are considered to be QoS violations.

Siljee *et al.* [30,215] propose a Dynamic Service Oriented Architecture (DySOA) which extends service-based systems to make them self-adaptive in order to maintain their functionality and ensure they meet their QoS requirements. The general activity diagram of the DySOA monitoring and adaptation process is depicted in Figure 2.4. This architecture first uses monitoring to track and collect information regarding a set of predefined QoS parameters (*e.g.* response time and failure rates), infrastructure characteristics (*e.g.* processor load and network bandwidth), and even a context (*e.g.* user GPS coordinates). The collected QoS information is analyzed and compared to the QoS requirements that are formalized in the SLA, *e.g.* the measured response time is simply compared to the required maximum response time. If the result of the QoS evaluation indicates that the QoS requirements are fulfilled, then monitoring continues. If one of the the QoS requirements is violated, a new configuration might be chosen that will satisfy the QoS requirements. Finally, the changes are enacted in the system. Possible changes are substituting a bound Web service for an alternative Web service or changing the structure and the flow of the Web service composition.

In [131,132], a middleware architecture is proposed to enable SLA-driven clustering of QoS-aware application servers in order to guarantee the QoS requirements and meet the SLAs of hosted Web services and applications. This middleware consists of three components which work as services, as depicted in Figure 2.5. The monitoring service observes at runtime the Web services and applications and verifies whether the QoS values meet the desired level to detect violations of SLAs, the load balancing service intercepts client requests to balance them among different cluster nodes, and the configuration service is responsible for managing the QoS-aware cluster. If the QoS values delivered by the cluster deviate from the desired level (*e.g.* the

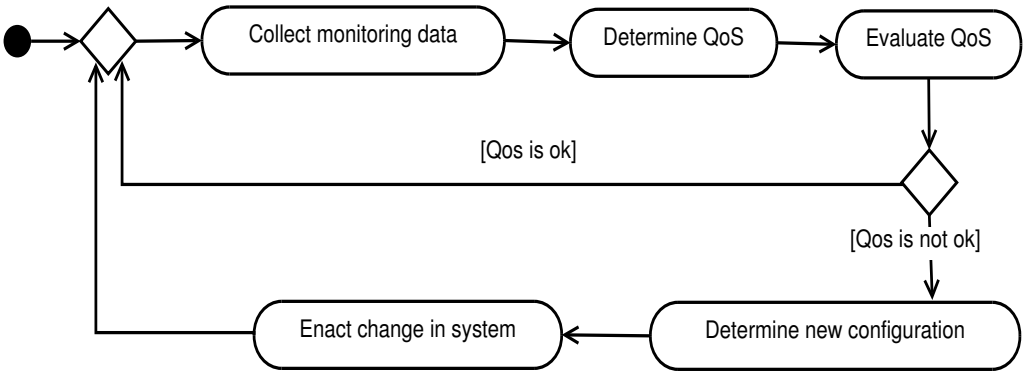


Figure 2.4: General activity diagram of the DySOA monitoring and adaptation process (Cf. [215])

response time breaches the predefined threshold), the middleware reconfigures that cluster by adding clustered nodes.

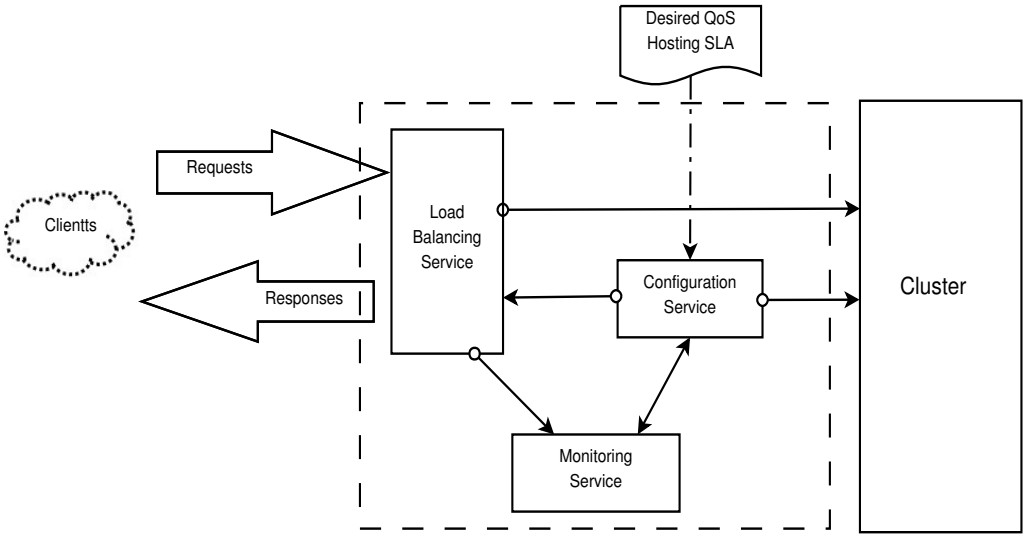


Figure 2.5: QoS-aware middleware services interaction (Cf. [132])

In his Master's thesis, Hilari [98] developed an architecture, which built on the SALMon[1] project [5], for monitoring the QoS information of a Web service and detecting SLA violations. This architecture consists of three services: Monitor, Analyzer, and Decision Maker. While the Monitor service collects the information about QoS attributes, the Analyzer service is responsible for checking any SLA

[1]http://appserv.lsi.upc.es/salmon/

violations in service-based systems. When a violation is detected, it is notified to the Decision Maker service of the affected system.

Michlmayr *et al.* [153] have presented an event-based QoS monitoring and SLA violation detection framework. This framework combines the advantages of client-side and server-side QoS monitoring, and it is integrated in the VRESCo[1] [152,154], which is a run-time environment for service-oriented computing. The framework observes the QoS values and checks whether they meet the required levels to detect possible violations of SLAs. Once an SLA violation is detected, notifications are sent to interested subscribers using E-Mail or Web service notification.

Recent studies [156, 224] propose autonomic frameworks to monitor QoS attributes and dynamically adapt service-based systems in an automated manner in response to QoS requirement violations. In [156], Mirandola and Potena propose a framework that dynamically adapts a service-based system while minimizing the adaptation costs and guaranteeing a required level of QoS. This framework triggers adaptation actions automatically in response to runtime violation of system QoS constraints, or the availability/non-availability of Web services in the environment. Thongtra and Aagesen [224] present a framework for Web service configuration that has *goals*, which express required performance and income measures, and *policies*, which define actions in states with unwanted performance and income measures. This framework monitors QoS attributes constraints and in the case of violations it triggers pre-defined policies.

2.2.1.2 Statistical Methods Based Approaches

A number of approaches have been proposed based on statistical methods in order to detect QoS violations. In contrast to threshold based approaches, these approaches observe the computed QoS values at runtime and use statistical methods in order to detect timely QoS violations with statistical confidence. In general, the statistical methods used by these approaches include relative frequency, hypothesis testing,

[1]Vienna Runtime Environment for Service-oriented Computing

and sequential probability ratio test [159, 232].

Mosincat *et al.* [161, 162] propose an approach, called ADULA, for transparent runtime monitoring, automated performance degradation detection, diagnosis, and repair for Web service compositions, which are expressed as BPEL (Business Process Execution Language) processes. The ADULA approach checks the fulfillment of SLA guarantees and determines if a violation has occurred using statistical hypothesis testing [159], implemented by a component called violation detectors. When a violation of SLA guarantees is detected, the approach diagnoses the cause of the violation and dictates repair actions, which include Web service replacement in subsequent process instances.

Authors in [8, 180, 181] propose an approach for the evolution and adaptation of Web services in order to provide the agreed QoS requirements stated in the SLA contract. This approach provides a compatibility mechanism that measures the aggregated satisfaction value of offered Web services to verify whether the QoS changes are satisfiable according to the existing contract. The approach uses fuzzy parameters to understand to what extent the QoS parameters are violated/satisfied and to compute the satisfaction function. Then, the degree of satisfaction function is evaluated. The existing contract will remain valid between the Web service provider and customer as long as the satisfaction value is more than the nominated in the contract. If the satisfaction value is less than the agreed value, the contract is voided and an adaptation/evolution strategy needs to be proposed such as Web service replacement.

Authors in [196] discuss some resource metrics for distributed systems that conform to the service-oriented concepts and cover various quality aspects. A QoS requirements satisfaction is analyzed by assessing the degree of SLA fulfilment or SLA violation danger. This degree is classified to a few distinct states. If the SLA is characterized as green, then all SLA conditions are fulfilled; yellow then SLA conditions are met but indicators come near to the predefined thresholds; or red then SLA conditions are not satisfied. Based on this classification of SLA status, the SLA

violation danger is measured as a ratio of the time for a Web service operation with yellow SLA to the time with yellow and green SLA.

Rosario *et al.* [25, 192] argue that QoS requirements are typically stated in the form of hard guarantees in SLA (*e.g.* response time always less than 2 seconds), however, experiments and measurements from existing Web services show evidence that soft guarantees, not hard, should be stated instead (*e.g.* response time less than 2 seconds in 95% of the cases). Therefore, they present the notion of soft probabilistic requirements (or contracts), especially for the performance attribute, in order to enable flexibility in SLA compliance. With this approach, QoS requirements are characterized by means of a set of selected quantiles of probability distributions for the QoS attributes. Moreover, they propose an approach to detect violations of the agreed SLA based on the statistical testing that depends on the empirical distribution function of the QoS attributes.

The work in [23, 24] proposes a generic application-independent framework for monitoring and analyzing QoS attributes of the Web services. The proposed framework has been adopted in the European WS-DIAMOND[1] project for providing self-healing solutions for service-based systems [24]. This framework provides models to detect QoS violations. These models use descriptive statistics, *e.g.* averages and standard deviations, to compute the QoS threshold as "average + standard deviation". Also, they use temporal patterns to avoid considering transient QoS violations. For instance, if there are only one or two values above the QoS threshold, they may not be classed as a violation; but if there are three successive values above the threshold, they are classified as such. Hence, this framework computes the thresholds at runtime to monitor the evolution of the given QoS characteristics more than their absolute values. It is worth noting that this approach proposes computing the threshold based on the descriptive statistics without statistical confidence, and there are not concrete rules for the proposed temporal patterns. However, this approach can be improved by using statistical methods, especially Shewhart control

[1]Web Services - DIAgnosability Monitoring and Diagnosis

charts methodology with Supplementary Runs Rules [157].

Schulz [206] proposes a metric, which is a linear function of given QoS thresholds, to quantify the degree of SLA fulfillment. This metric takes into account the underlying structure of the SLA as well as the available options for monitoring QoS attributes. Using this metric, it becomes possible at runtime to obtain detailed information of the status of a Web service compliance. This approach gives a percent of satisfying QoS requirements, which might speed the detection of QoS violations by continuously monitoring the satisfaction level.

Chan *et al.* [48] propose an approach that provides a rich platform in .NET applications for monitoring QoS requirements by checking constraints written in PCTL (Probabilistic Computation Tree Logic) [94]. Its methodology is simply calculating the relative frequencies of successful and unsuccessful monitoring results, and then comparing them with the required probability. Based on these calculated relative frequencies and the required probability, it decides whether the QoS requirements are satisfied. It is worth mentioning that, this approach can be further improved by using the sequential hypothesis testing as a good method to make statistically significant decisions [232].

Sammapun *et al.* [200, 201] propose an approach, which is called MaC, adopts statistical hypothesis testing for verifying QoS requirements defined in a probabilistic extension of the Meta-Event Definition Language (MEDL). The main idea of this approach is to sample many execution paths, estimate the probability of success, and then apply hypothesis testing method to check for probabilistic property and make statistically significant decision regarding this property with a given confidence level. Using this methodology, it is able to investigate properties with a single probabilistic operator and provide p-value for the significance of the testing outcome-based-decision. To overcome false alarms problem resulted from considering too many samples, it uses the sliding window that keeps the number of samples used in monitoring constant and pre-defined.

Grunske and Zhang [87] propose a monitoring framework called ProMo (Prob-

abilistic Monitoring). This framework adopts a probabilistic temporal logic called CSL^{Mon}, which is a subset of the continuous stochastic logic (CSL) [15, 17], to define probabilistic properties. It samples execution paths and checks whether the probabilistic properties are satisfied using acceptance sampling and sequential probability ratio test (SPRT) [232] with given confidence and power levels. Sequential hypothesis testing is considered the most effective testing procedure with respect to the number of execution paths needed to apply the test and check the correctness of probabilistic properties [244]. Therefore, this approach has some relative advantages over the other statistical methods based approaches. Further improvement for this approach has been proposed by Grunske [86] to support continuous monitoring and minimize the number of required samples and the runtime overhead to reach a decision.

2.2.1.3 Summary and Limitations of Reactive Approaches

The reactive approaches reviewed above are summarized in Table 2.1. Based on the summary, some observations can be highlighted:

- *Web services*: Most of the reviewed reactive approaches are applied to composite Web services (or service-based systems), and only three approaches are applied to individual Web services. It is worth mentioning that the approaches proposed by Chan *et al.* [48], Sammapun *et al.* [200, 201], and Grunske and Zhang [86, 87] for runtime verification of QoS attributes are applied generally to software systems and not specifically to Web services. However, the work of Grunske and Zhang [86, 87] has been already integrated into the QoSMOS (QoS Management and Optimization of Service-based systems) framework [37] that is proposed for the development of adaptive service-based systems.

- *QoS attributes*: Performance, reliability, and availability are the main three QoS attributes that are considered by the reviewed approaches, respectively. In addition, some approaches claim that other QoS attributes can be added

and considered by the proposed approaches.

- *Application domain*: The application domains of the reviewed reactive approaches are mainly three: (1) SLA management, (2) Adaptation of Web services or service-based systems, and (3) Runtime verification of QoS attributes. However, the adaptation domain is the most targeted by the proposed approaches.

- *MAPE-K autonomic control loop*: The summary in Table 2.1 shows that the reviewed approaches implement some or all of the activities of the MAPE-K autonomic control loop. In general, all the approaches implement the "Analyze" activity, and most of the approaches proposed in the adaptation domain implement the four activities of the MAPE-K loop.

- *How QoS data is obtained*: Most of the reviewed approaches use the QoS data that is collected from the provider-side. Other approaches use the QoS data that is collected from the client-side, both client-side and provider-side, or not specified.

- *Probability distribution*: As mentioned above, the statistical methods based approaches report that the observable QoS attributes are probabilistic in nature, and therefore they can be represented by a probability distribution. However, the summary shows that few approaches evaluate or consider the probability distribution of the QoS attributes.

- *Serial dependency*: Since the QoS data is collected over time, it is expected to be serially dependent. However, the reviewed statistical methods based approaches use the statistical methods such as hypothesis testing and sequential probability ratio test that assume the data is independent without evaluating this assumption. Note that Grunske and Zhang [87] acknowledge this limitation and mention that they will address in their future work.

	Threshold Based						Statistical Methods Based								
	Siljee *et al.* [30, 215]	Lodi *et al.* [131, 132]	Hilari [98]	Michlmayr *et al.* [153]	Mirandola and Potena [156]	Thongtra and Aagesen [224]	Mosincat *et al.* [161, 162]	Pernici *et al.* [8, 180, 181]	Rud *et al.* [196]	Rosario *et al.* [25, 192]	Halima *et al.* [23, 24]	Schulz [206]	Chan *et al.* [48]	Sammapun *et al.* [200, 201]	Grunske and Zhang [86, 87]
1. Web Service	C	C	C	I	C	C	C	C	I	C	C	I	N	N	N
2. QoS															
Performance	✓	✓	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	✓	∼	∼
Reliability	×	×	×	×	✓	×	✓	✓	✓	×	×	×	∼	✓	✓
Availability	✓	✓	✓	✓	×	×	×	×	×	×	×	✓	∼	∼	∼
3. Application	A	A	A	S	A	A	A	A	S	S	A	S	V	V	V
4. MAPE-K															
Monitor	✓	✓	✓	✓	✓	✓	✓	×	×	✓	✓	×	×	×	×
Analyze	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Plan	✓	✓	✓	×	✓	✓	✓	✓	×	×	×	×	×	×	×
Execute	✓	✓	✓	×	✓	✓	✓	✓	×	×	×	×	×	×	×
5. Data	Cl	Pr	Pr	CP	Pr	Pr	Cl	N	Pr	Pr	CP	N	Pr	Pr	Pr
6. Distribution							×	×	×	✓	×	×	×	✓	✓
7. Dependency							×	×	×	×	×	×	×	×	∼

(C) Composite, (I) Individual, (N) Not specified, (✓) Supported, (×) Not supported, (∼) Can be supported, (A) adaptation, (S) SLA management, (V) Runtime Verification, (Cl) Client side, (Pr) Provider side, (CP) Client side and Provider side.

Table 2.1: Summary of reactive approaches

In general, the reactive approaches detect violations of QoS requirements after they have occurred. Therefore, this reactive detection of violations leads to critical issues. For example, SLA management cannot avoid costly compensation and repair activities resulting from violating SLA contracts. In addition, adaptation is triggered

after violations and problems have already occurred. In particular, such reactive adaptations have several important drawbacks that are discussed in literature [97, 111, 149, 204]. These drawbacks can be summarized in the following:

1. Reactive adaptations might come too late to the extent that faulty Web service or service-based system are executed, which can lead to undesirable consequences such as loss of money or transactions and unsatisfied users as well as might require the execution of additional activities such as compensation or roll-back [111, 149].

2. In an emergency situation such a reactive adaptation can lead to critical situations. For example, it might delay the timely dispatch of operational forces, *e.g.* fire engines or ambulances [204].

3. In some cases the reactive detection of violations is very late to the extent that an adaptation of the system is not possible anymore, because the system has already terminated in an inconsistent state [97].

4. In some cases executing adaptation activities reactively can considerably increase execution time compared to executing activities before violations occur, and therefore might reduce the overall performance of the running Web service or service-based system [97].

2.2.2 Existing Approaches for Proactive Detection of QoS Violations

In order to address the limitations of the existing reactive approaches, some approaches have been proposed for the proactive detection of potential QoS violations. Generally, the proactive approaches aim to prevent SLA violations and support proactive adaptation. Preventing SLA violation refers to that the SLA management predicts a menacing SLA violation and proactively performs preventive actions in order to avert the violation before it occurs [204]. On the other hand, proactive

adaptation means the Web service or service-based system will detect the need for adaptation and will self-adapt before a violation of QoS requirements will occur or lead to undesired consequences [178].

As mentioned above, the proposed approaches for proactive detection of potential QoS violations can be classified into three main groups: (1) Online testing based approaches, (2) Machine learning based approaches, and (3) Time series modeling based approaches. In the following, these approaches are summarised with some details about their underlying methodology, advantages, and shortcomings.

Online Testing Based Approaches

Online testing based approaches [65,97,149,150,202] exploit online testing techniques to detect QoS violations before they occur in order to proactively trigger adaptation requests. Online testing means that the Web service or service-based system is tested (*i.e.* fed with dedicated test input) in parallel to its normal use and operation [147]. The main idea behind using the online testing is that an online test can detect a violation if a faulty Web service instance is invoked during the test. This points to a potential problem that the service-based system might face in the future of its operation when invoking this faulty Web service instance. In such a case, adaptation activities can be proactively triggered to prevent the potential violation. These adaptation activities might include replacing the faulty Web service instance with another instance or changing the Web service composition.

The online testing based approaches rely on three assumptions, which are [149]:

- Assumption 1: Each failure of a constituent Web service of a service-based system leads to a requirement violation of that service-based system and thus the need for an adaptation arises.

- Assumption 2: The observed elements provide a notification in case of any change which would invalidate the testing data, such as a new version of the Web service implementation.

- Assumption 3: Invoking the constituent Web services of a service-based system for test purposes will have no side effects, such as when testing a book delivery Web service, no books would actually be delivered as a result of the testing activities.

Metzger *et al.* discussed that the online testing assumptions can be relaxed and mitigated as presented in their work [149]. However, they are still hard to be typically fulfilled and hold for the real application of service-based systems. In addition to these assumptions, there are some shortcomings related to online testing that might limit the practical applicability of these approaches. These shortcomings are:

- *Providing only general statements*: Online testing can provide only general statements about Web services or service-based systems but not about their current execution traces as can be achieved by monitoring approaches [27, 163]. This point is already raised in the literature and discussed as one of the advantages of monitoring approaches over testing [59]. Therefore, some failures and violations cannot be uncovered and might escape testing because the concrete input that leads to the current execution trace might not be covered by any test case [149].

- *Requiring additional costs*: Online testing applied to service-based systems might lead to additional costs. This is because the service-based systems often include external Web services whose invocations are associated with costs [149].

Machine Learning Based Approaches

Machine learning based approaches [118, 119, 120, 121, 122] use techniques from the areas of machine learning [96] to construct prediction models in order to proactively detect potential violations of QoS requirements and agreed SLA contracts. These approaches leverage machine learning capabilities to train prediction models using previously monitored historical QoS data. For example, collected historical QoS

data can be fed into multi-layer artificial neural networks [96] as training dataset in order to generate predictions of the future SLA violations.

The effectiveness of machine learning based approaches relies on the historical QoS data, which is required as a training dataset, and the training process [204]. For ensuring the expected accuracy of the SLA violation prediction, several hundreds or, in some cases, even thousands of QoS data points are necessarily required to train prediction models. Indeed, this can limit the applicability of these approaches if only a small amount of historical data is available [204]. Moreover, the prediction models have to be re-trained after each adaptation of the service-based systems, which is a time-consuming and computationally intensive process [165].

Time Series Modeling Based Approaches

Several approaches (*e.g.* [73, 80, 218, 251, 252]) have been proposed based on time series modeling for proactive detection of potential QoS violations, especially linear ARIMA (Autoregressive Integrated Moving Average) models [33]. Simply, the key idea of these models is to fit the past monitored QoS measures in order to forecast their future values and violations of predefined requirements. Time series models can be applied for QoS measures starting with 30 historical observations and can give acceptable forecasting accuracy [33]. The main advantage of the time series modeling based approaches is that they In addition, they are data-oriented approaches and do not impose any restrictive assumptions on the environment of the Web service or service-based system. Moreover, because time series modeling's methodology is based on standard statistics theory and probability distributions, prediction models can be straightforwardly implemented without a time-consuming learning stage as is the case with machine learning models.

These three groups of approaches can be briefly compared in different dimensions, as depicted in Table 2.2. First, based on the cost in terms of the computational overhead (and the additional cost associated with the invocations of external Web services), the online testing based approaches are the most expensive, followed

by the machine learning based approaches. Statistical methods based approaches are the least expensive. Second, online testing based approaches are environment-dependent, whereas machine learning based approaches and time series modeling based approaches are not. The third dimension is timeliness which means how fast the approach can be used to detect potential violations of QoS requirements. Based on the timeliness, the online testing based approaches are the best because they do not require historical QoS data to be applied, followed by the time series modeling based approaches which require less historical QoS data to construct a forecasting model compared to the machine learning based approaches.

Approaches	Cost	Enviroment-Dependant	Timeliness
Online Testing Based	(3)	Yes	(1)
Machine Learning Based	(2)	No	(3)
Time Series Modeling Based	(1)	No	(2)

(i) Rank "i" among the approaches.

Table 2.2: Summary of proactive approaches

Based on this brief comparison, it can be seen that the time series modeling based approaches are promising in their ability to provide accurate forecasting for QoS attributes and potential violations of their requirements. Indeed, the accurate QoS forecasting is essentially required in order to avoid violating SLA constraints, missing proactive adaptation opportunities, and executing unnecessary proactive adaptations. In particular, missing a proactive adaptation opportunity due to inaccurate QoS forecasting can obviously lead to the same shortcomings as faced in the setting of reactive adaptations, *e.g.* it can require costly compensation or repair activities. Eventually, this would diminish the benefits of proactive adaptation [147]. Moreover, unnecessary adaptations can lead to critical shortcomings [147, 148, 149]:

- First, unnecessary adaptations can be costly even in the proactive setting, especially when a seemingly unreliable but cheap Web service is replaced by a more costly one. Moreover, additional activities, such as SLA negotiation for

the alternative Web services, might have to be achieved [149].

- Second, unnecessary adaptations may lead to instabilities in the software system which can lead to unreliable and inconsistent behavior. Therefore, unnecessary adaptations should be avoided [149].

Consequently, the goal of this thesis is to propose an efficient time series modeling based QoS forecasting approach that can accurately forecast QoS attributes and potential violations of their requirements. Accordingly, in the following we review the existing time series modeling based approaches and identify the main challenges that have to be addressed to achieve this goal.

2.2.2.1 Existing Approaches Based on Time Series Modeling

Time series modeling based proactive approaches have been presented as a promising technique to predict future QoS values in order to support proactive adaptation of service-based systems, SLA management, failure management, and QoS-based service selection and composition in dynamic environments. Zeng *et al.* [250] investigate performance metrics that can be predicted based on their historical data and using time series models. Their work introduces the design and implementation of an event-driven QoS prediction system, which can process operational service events in a real-time fashion, in order to predict or refine the prediction of performance metrics. Recently, Solomon and Litoiu [218] present a dynamic predictive model based on linear regression and ARIMA models to predict with more confidence system performance degradations. They also propose a feedback based evolution architecture that can proactively, using these performance degradations predictions, tune and optimize software systems.

Current studies [72, 73, 147, 252] propose failure prediction techniques to enable and enhance proactive failure management by avoiding possible failures. In [72, 73], Fu and Xu develop two models: (1) Spherical covariance model with an adjustable timescale parameter in order to quantify the temporal correlation, and (2) Stochastic

model in order to characterize spatial correlation. Therefore, they become able to cluster failure events based on their correlations and predict their future occurrences using time series autoregressive models. In addition, Zhang and Fu [252] propose a framework for autonomic failure management. They equip the framework with the failure prediction functionality in order to achieve proactive self-management of both failures and resources in networked computer systems. This framework analyzes node, cluster, and system failure behaviors. Then, based on quantified failure dynamics, it forecasts prospective failure occurrences using linear time series models, especially autoregressive models.

Recently, Metzger *et al.* [147, 148] discuss two directions along which accurate proactive adaptations can be achieved. These two directions are: (1) Improving the failure prediction techniques that trigger the need for adaptations, and (2) Estimating the accuracy of the predicted failures at runtime. While Metzger *et al.* in this work use only simple prediction models such as the arithmetic average and simple exponential smoothing, they recommend using the advanced time series prediction models in future work.

In the context of QoS and SLA management, Nobile *et al.* [166] propose an architecture that supports QoS for RT-RPCs (Real-Time Remote Procedure Calls), which are widely used in the implementation of distributed applications. To enable proactive management, the architecture uses ARIMA models in order to predict future traffic characteristics of RT-RPCs that pass through the proxy. Therefore, the architecture is furnished with the capability of allowing the anticipated and rational allocation of the necessary resources to attend the predicted demand. In [257], Zhu *et al.* present a framework that is designed to help predict the performance of parallel/distributed discrete event simulation (PDES) applications. In particular, the framework uses linear time series analysis to forecast the future performance of PDES in order to proactively evaluate and optimize the QoS of PDES programs.

In the domain of QoS-based Web service selection and composition, Vu *et al.* [231] present a QoS-based Web service selection and ranking approach, which uses trust

and reputation evaluation techniques as well as linear regression models in order to predict the future QoS of Web services. Based on the predicted QoS values, the approach selects and ranks the Web services. The output is a list of Web services which fulfill QoS requirements of a user and are ordered by their prospective satisfaction levels of the given QoS criteria. Li *et al.* [123] propose a Web service selection algorithm based on a QoS prediction mechanism. This algorithm uses time series modeling based on structural equations to fit QoS values of Web services, and dynamically predicts their future changes in order to support adaptive Web services selection. In addition, Godse *et al.* [80] propose a method that combines monitoring and extrapolation methodologies based on ARIMA models to predict Web service performance. This method is used to support automating dynamic service selection methodology, which is robust in the face of varying QoS.

As an evaluation for the existing QoS forecasting approaches based on time series modeling, Cavallo *et al.* [46] present an empirical study aimed at comparing different approaches for QoS forecasting. Specifically, the approaches being compared are: (1) The averaged value from past monitored QoS data, (2) The last observed QoS value which is referred to as "current QoS value", (3) linear regression model, and (4) Time series ARIMA model. The study is performed on QoS data obtained by monitoring the execution of ten real Web services for four months. It concludes that ARIMA forecasting is the best compromise in ensuring a good prediction error, being sensible to outliers, and being able to predict likely violations of QoS constraints.

2.2.2.2 Summary and Limitations of Time Series Modeling Based Approaches

The time series modeling based proactive approaches reviewed above are summarized in Table 2.3, and some observations can be highlighted in the following:

- *Web services*: Most of the reviewed approaches are applied to Web services (especially individual Web services). However, some approaches are applied generally to software systems and not specifically to Web services.

- *QoS attributes*: Similarly to reactive approaches, Performance, reliability, and availability are the main three QoS attributes that are considered by the reviewed proactive approaches, respectively.

	Zeng *et al.* [250]	Solomon and Litoiu [218]	Fu and Xu [72, 73]	Zhang and Fu [252]	Metzger *et al.* [147, 148]	Nobile *et al.* [166]	Zhu *et al.* [257]	Vu *et al.* [231]	Li *et al.* [123]	Godse *et al.* [80]	Cavallo *et al.* [46]
1. Web Service	✓	✓	×	×	✓	×	×	✓	✓	✓	✓
2. QoS											
Performance	✓	✓	×	×	✓	✓	✓	✓	×	✓	✓
Reliability	×	×	✓	✓	×	×	×	×	✓	×	×
Availability	×	×	×	×	×	×	×	×	✓	✓	×
3. Application	S	A	F	F	A	A	A	Se	Se	Se	Se
4. MAPE-K											
Monitor	✓	✓	×	×	×	✓	×	×	×	✓	×
Analyze	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Plan	×	✓	×	×	×	✓	×	×	×	×	×
Execute	×	✓	×	×	×	✓	×	×	×	×	×
5. Data	Cl	Pr	Pr	Pr	Cl	Pr	Pr	Cl	Pr	CP	Cl
6. Distribution	×	×	×	×	×	×	×	✓	×	✓	×
7. Dependency	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
8. Stationarity	×	✓	×	×	×	✓	×	×	×	✓	✓
9. Nonlinearity	×	×	×	×	×	×	×	×	×	×	×

(✓) Supported, (×) Not supported, (A) adaptation, (S) SLA management, (F) Failure management, (Se) Service selection, (Cl) Client side, (Pr) Provider side, (CP) Client side and Provider side.

Table 2.3: Summary of time series modeling based proactive approaches

- *Application domain*: The reviewed proactive approaches are proposed in different application domains, which include SLA management, adaptation of

Web services (or generally software systems), failure management, and service selection and composition.

- *MAPE-K autonomic control loop*: The reviewed approaches implement the "Analyze" activity, and only a few approaches implement other activities of the MAPE-K loop.

- *How QoS data is obtained*: The reviewed proactive approaches use the QoS data that is collected from the provider-side, client-side, or both client-side and provider-side, respectively.

- *Probability distribution*: Only two approaches consider the probability distribution of the QoS data.

- *Serial dependency*: All the reviewed approaches assume the QoS data is serially dependent, and introduce time series modeling to predict future values.

- *Stationarity*: Broadly speaking, stationarity means that the mean and the variance of the data are constant over time and its autocovariance is not time varying and is only a function of the time distance between the observations [67, 167]. Stationarity enables the time series model to estimate the mean, variance, and other parameters by averaging across the single realization of the data, which explains why the time series models assume the data is stationary or can be stationarized using transformation methods [33]. However, only few of the reviewed approaches mention and check the stationarity of the QoS data.

- *Nonlinearity*: Time series models are traditionally divided into two classes; linear and non-linear, and specifying the class that can be used should be based on evaluating the QoS data. Practically, linear time series models are easier to use. This may be why none of the reviewed approaches evaluate the nonlinearity of the QoS data and rather use linear time series models.

In general, authors of the existing time series modeling based approaches conclude that time series models are initially a good statistical tool to model the dynamic behavior of QoS attributes and forecast their future values. However, Godse *et al.* [80] report that studying the dynamic characteristics of QoS attributes and proposing an efficient QoS forecasting approach is a crucial need in order to support proactive QoS management and Web service selection. Moreover, Cavallo *et al.* [46] conclude based on their empirical study that a good forecasting of QoS violations is still a challenging issue and further approaches able to better deal with this issue should be investigated.

Based on our review of these existing proactive approaches, we can summarize their main limitations as follows:

- Although QoS attributes are mentioned that are probabilistic and have stochastic characteristics, these stochastic characteristics are not studied or evaluated based on real QoS data. This evaluation of QoS stochastic characteristics is very important to select and use an appropriate time series model that can adequately fit QoS attributes and accurately forecast their future values.

- Only linear time series models, especially ARIMA models, are used by these approaches. Moreover, these linear models are mostly used without checking their underlying assumptions or evaluating their adequacy. This implies that using time series models without satisfying their assumptions can provide inaccurate forecasts, which in turn leads system management to take inappropriate or unnecessary actions based on incorrect information.

- There is no discussion of how those linear time series models can be constructed at runtime as well as how they can be continuously updated based on evaluating their adequacy and forecasting accuracy.

Addressing these limitations is very important to guarantee accurate forecasting for QoS attributes and potential violations of their requirements. Therefore, the

goal in this thesis is to propose a forecasting approach for QoS attributes that can address the above limitations and provide accurate QoS forecasting. In the rest of this thesis, the main challenges of achieving this goal are formulated into research questions and then addressed as contributions of the thesis. The outcome of addressing these research questions is a collection of QoS characteristic-specific forecasting approaches based on time series modeling that construct together a general automated forecasting approach. This general forecasting approach will be able to fit different dynamic behavior of QoS attributes in order to forecast their future values and potential violation of their requirements.

2.3 Summary

This chapter first presented the background of the contents presented in the remainder of the thesis, starting with a brief introduction to Web services, compositions, and service-based systems. Then, because the Web services and service-based systems are characterized by QoS attributes in addition to functionality specifications, the chapter described different aspects related to QoS attributes, including QoS definition and classification, monitoring approaches for QoS attributes, and the importance of using QoS attributes for Web services and service-based systems.

The second part of the chapter reviewed the existing approaches for detecting violations of QoS requirements. These approaches are classified into reactive approaches that are based on monitoring techniques and proactive approaches that are based on anticipating potential QoS violations. In particular, it reviewed in detail the existing time series modeling based proactive approaches and highlighted their limitations. These limitations represent the challenges that have to be addressed in this thesis in order to provide accurate QoS forecasting.

Chapter 3

Research Methodology

The previous chapter presents the background on Web services, composition, QoS attributes, and adaptation of service-based systems followed by a review of the existing reactive and proactive detection approaches for QoS violations and a discussion of their limitations. These limitations are related to providing accurate forecasting for QoS attributes and potential requirements violations. Accordingly, in order to address the limitations of the existing approaches, the goal of this research is *"to develop a general automated statistical forecasting approach based on time series modeling for QoS attributes"*. This forecasting approach will automatically fit the dynamics of QoS attributes in order to accurately forecast their future values and detect proactively potential future violations of QoS requirements. Achieving this goal is key prerequisite to support proactive SLA management, proactive service selection and composition, and the proactive adaptation of Web services or service-based systems.

In order to achieve the overall research goal, a number of research questions need to be addressed. Indeed, explicitly formulating the research questions helps structure the research activities and highlights the novelty of a solution and the contributions of the research work [79, 209]. Therefore, the next section formulates the research questions that have to be addressed in the thesis, followed by an overview of the research approach that is applied in order to address these formulated research

questions. Finally, the strategy used to evaluate the contributions in this thesis is discussed at the end of the chapter.

3.1 Research Questions

The research goal is planned to be achieved by formulating the limitations of existing proactive approaches into refined research questions that will be addressed in the thesis. These research questions are discussed as follows.

■ **RQ1**. *To what extent do the QoS attributes of real-world Web services exhibit stochastic characteristics related to time series modeling?*
From a statistical standpoint, proposing an efficient and accurate forecasting approach that fits the QoS attributes and forecasts their future values requires the key stochastic characteristics of these attributes to be identified and evaluated. This is because the accuracy of the proposed forecasting approach is statistically based on the QoS stochastic characteristics. Based on th literature of time series analysis and modeling (*e.g.* [33, 103, 158, 184]), we identify a number of key stochastic characteristics that have to be considered in order to guarantee accurate forecasting. These stochastic characteristics include probability distribution, serial dependency, stationarity, and nonlinearity. In Chapter 2, we introduced these stochastic characteristics and checked whether the existing approaches studied or evaluated them. We concluded that one of the main limitations of the existing proactive approaches is that they do not study or evaluate these characteristics based on real-world QoS datasets. We therefore necessarily need to evaluate to what extend the QoS attributes of Web services exhibit these stochastic characteristics based on real-world QoS datasets.

■ **RQ2**. *What are the adequate time series models that can be used to characterize the given QoS attributes and correctly forecast their future values?*
Time series modeling literature is rich and traditionally divided into two classes: linear and non-linear time series modeling. For the given QoS attributes, it has to

specify the adequate time series models that can be used to fit and forecast the future values. Indeed, specifying the class of adequate time series models cannot be decided a priori but should be based on the outcome of addressing the **RQ1**, which represents the stochastic characteristics of the given QoS attributes. In other words, specifying the class of adequate time series models is data-oriented and depends mainly on the evaluated stochastic characteristics of the QoS data under analysis.

■ **RQ3**. *How can the used time series models be automatically constructed at runtime?*

The construction of time series models is typically an iterative and human-centric process [33]. However, forecasting QoS attributes needs to occur at runtime in a timely and continuous manner. It is very difficult to achieve this using manual iterative methods requiring human intervention. Therefore, it is necessary to develop an effective automated procedure for automatically constructing the used time series models in less time.

■ **RQ4**. *How can the adequacy and forecasting accuracy of the constructed time series model be continuously evaluated at runtime?*

The stochastic characteristics of the QoS attributes are affected or caused by uncontrolled factors of the software systems or Web services and their context [22, 192]. This implies that there is no guarantee that the stochastic behavior of the given QoS data will remain constant over time. Therefore, the adequacy and forecasting accuracy of the constructed time series model need to be continuously evaluated at runtime in order to immediately re-specify and re-construct another appropriate model in the case of reporting inadequacy or low forecasting accuracy.

3.2 Research Approach and Solution

In order to achieve the research goal of proposing general automated forecasting approach for QoS attributes, this research project investigates how to address the above formulated research questions. In the rest of this section, we discuss how each

research question is addressed.

3.2.1 Evaluating Stochastic Characteristics of QoS Attributes

The evaluation of the stochastic characteristics of QoS attributes should be conducted by applying appropriate statistical methods/tests to real-world QoS datasets in order to assess real representative characteristics. We have reviewed the literature in order to know whether real-world QoS datasets are available and can be used in the current research. The review reveals that there are mainly three benchmark datasets have been studied, and are publicly available. These three benchmark datasets are briefly discussed in the following:

1. QoS dataset-1 of ten Web services [46] which is collected by invoking the Web services every hour for about four months, and then the response time and number of failures are computed. Indeed, this dataset includes about 2,900 observations of response time only a few of which indicate service failure. Therefore, this dataset has limitations to be used in the planned evaluation: (1) Sufficient number of observations for the time between failures cannot be computed because only few failures occur during the time of invocation, and (2) Ten Web services are not enough to generalize the evaluation results.

2. QoS dataset-2 of 100 Web services [255] which is collected by invoking the Web services sequentially 100 times, and then the response time and number of failures are computed. Accordingly, this dataset includes only 100 observations of response time and records very few failures. Although the number of Web services is acceptable and larger than that in the QoS dataset-1, the number of observations of response time is small, *i.e.* only 100 observations. In addition, the time between failures datasets cannot be computed because only very few failures occur during the time of invocation. This makes this QoS dataset inappropriate for our purpose.

3. QoS dataset-3 of 2,507 Web services [2, 3] which is collected by invoking the Web services every ten minutes for about three days. Based on the invocation results, some QoS attributes are computed such as response time, latency, throughput, availability, and reliability. However, original dataset is not available with only the average of these attributes being accessible online[1]. In other words, in this dataset only one observation is available for each QoS attribute. Therefore, this QoS dataset does not fit on the current objective of evaluating the QoS stochastic characteristics.

In conclusion, we are not aware of any pre-existing real-world QoS datasets that can be used to evaluate the QoS stochastic characteristics, aiming at significant generalization. In order to address this problem, we plan to generate our own primary QoS datasets by invoking 800 real-world Web services to collect sufficient response time and time between failures datasets. We then apply statistical methods/tests to collected QoS datasets in order to evaluate the aforementioned stochastic characteristics.

In order to evaluate probability distribution of the QoS attributes, we first need to specify the distributions that can be fitted for the QoS attributes and the fitting method that can be used. Generally, we will consider various probability distributions for the QoS attributes which include exponential, gamma, weibull, log-logistic, non-central student's t, and normal. In addition, we will adopt the maximum likelihood estimation method [4, 38] to fit these distributions because of the generally good properties of its estimates compared to other existing estimation methods [76]. In order to evaluate the serial dependency of QoS attributes, we will use the runs test [233] proposed by Wald and Wolfowitz.

Stationarity can be evaluated in practice by individually checking for stationarity in the mean and in the variance. More specifically, QoS data is stationary in the mean when it has constant mean (no trend) over time, while it is stationary in the variance when it has constant variance (same variation) over time. In order to

[1]http://www.uoguelph.ca/ qmahmoud/qws/index.html

evaluate the *stationarity in the mean*, we will use Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test [115]. On the other hand, we will use the Engle test [68] in order to evaluate the *stationarity in the variance*. Finally, in order to evaluate the nonlinearity of QoS attributes, we will use the Hansen test [91, 92].

3.2.2 Specifying Class of Adequate Time Series Models

As mentioned above in **RQ2**, specifying the class of adequate time series models depends on the evaluated stochastic characteristics of QoS attributes. In particular, we classify the evaluated stochastic characteristics of QoS attributes into two groups: (1) One is related to the underlying assumptions of the time series modeling, which includes probability distribution, serial dependency, and stationarity in the mean; and (2) The other can be used to specify the class of adequate time series models, which includes stationarity in the variance and nonlinearity.

Before specifying the class of adequate time series models, it is necessary to check to what extent the QoS data fulfils the underlying assumptions of time series models. These assumptions include normality, serial dependency, and stationarity in the mean. Fulfiling these assumptions by the QoS data is considered as a general requirement in order to use time series models for accurately fitting and forecasting QoS attributes. Where these assumptions are violated, transformation methods need to be applied. For example, if the given QoS data is non-normally distributed, the power transformation [32] can be applied to achieve normality.

Once the underlying assumptions are fulfilled, the class of adequate time series models can be specified based on evaluating the nonlinearity and stationarity in the variance. It is worth mentioning that the non-stationarity in the variance mentioned in this work is called volatility clustering [68]. More specifically, there are four combinations of stochastic characteristics that can be identified for QoS attributes as follows:

1. Linearly dependent and stationary in the variance: Linear time series models can be specified in this case.

2. Nonlinearly dependent and stationary in the variance: Nonlinear time series models can be specified in this case.

3. Linearly dependent and non-stationary in the variance: Linear time series models along with time series models that characterize volatility clustering can be specified in this case.

4. Nonlinearly dependent and non-stationary in the variance: Nonlinear time series models along with time series models that characterize volatility clustering can be specified in this case.

As discussed in the related work in Chapter 2, only the first type of stochastic characteristics has been addressed in the literature through the application of linear time series models, especially ARIMA models, to fit and forecast QoS attributes. Therefore, it is necessary to evaluate and address the last three types - as we do in this thesis.

3.2.3 Constructing Adequate Time Series Models

In order to address the **RQ3**, we have reviewed the time series modeling literature and found that Box and Jenkins [33] proposed a well-established procedure for constructing an adequate time series model for the given time series. This procedure is known as the Box-Jenkins methodology [158]. The Box-Jenkins methodology consists of four phases:

(P1) Identification phase, where the order of the time series model is determined.

(P2) Estimation phase, where the parameters of the identified model are estimated.

(P3) Diagnostic checking, where the adequacy of the estimated model is examined.

(P4) Prediction phase, where the model is used to forecast the future observations.

As stated above, there are underlying assumptions for the time series models; and in some cases to satisfy these assumptions, data transformations and preparation

activities are needed. Consequently, a preliminary phase of data preparation (P0) is added to the Box-Jenkins methodology resulting in five phases [137]. The process of these five phases is depicted in Figure 3.1.

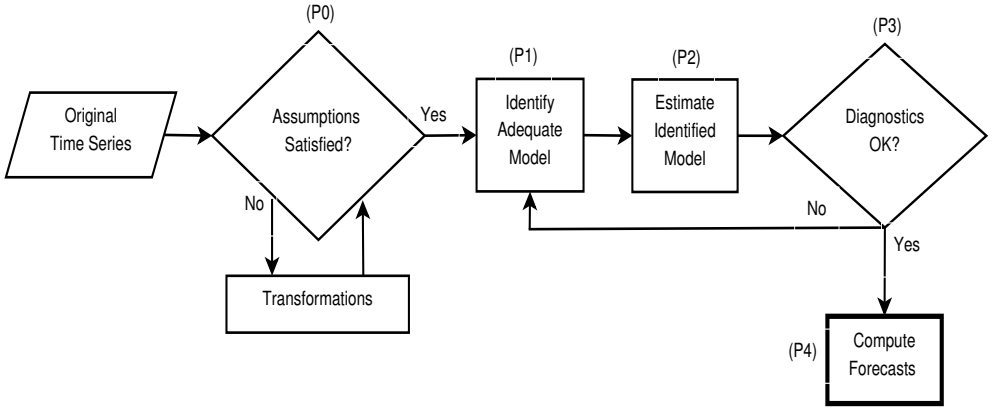


Figure 3.1: Box-Jenkins procedure for constructing adequate time series model

It is clear from Figure 3.1 that the Box-Jenkins procedure involves manually identifying a model, estimating its parameters, and checking its adequacy. If this model is not adequate, it goes back to the identification phase and another model is re-identified. This process is a time-consuming iterative cycle of identification, estimation, checking and re-identification, which is infeasible if automated runtime QoS forecasting is required. Therefore, this research project builds on the Box-Jenkins methodology and proposes a parallelized procedure for constructing an adequate time series model, as depicted in Figure 3.2. This proposed procedure based on statistical methods identifies and estimates a set of time series models which can be used to fit the QoS data under analysis. It then checks the diagnostics of the estimated models and selects the best one based on an information criterion [1]. The main goal of the proposed procedure is to solve the iterativeness and human intervention issues in order to automatically and quickly construct the adequate time series model and forecast the future values of the given QoS time series dataset.

As explained in Figure 3.2, the proposed procedure consists of six phases:

(P1) Preliminary phase (data preparation): The underlying assumptions of time se-

ries models are verified, and if they are not satisfied some data transformations are performed.

(P2) Identification phase: A set of adequate time series models is identified based on auto-correlation function (ACF) and partial auto-correlation function (PACF) [33, 214].

(P3) Estimation phase: Parameters of the identified models are estimated using one of the well-established statistical estimation methods such as the maximum likelihood estimation method [4, 38].

(P4) Diagnostics phase: Adequacy of the estimated models is examined in terms of various diagnostic aspects.

(P5) Best model selection phase: The best model among the estimated and examined ones is selected based on an information criterion [1].

(P6) Prediction phase: The selected model is used to forecast the future values of the QoS data under analysis.

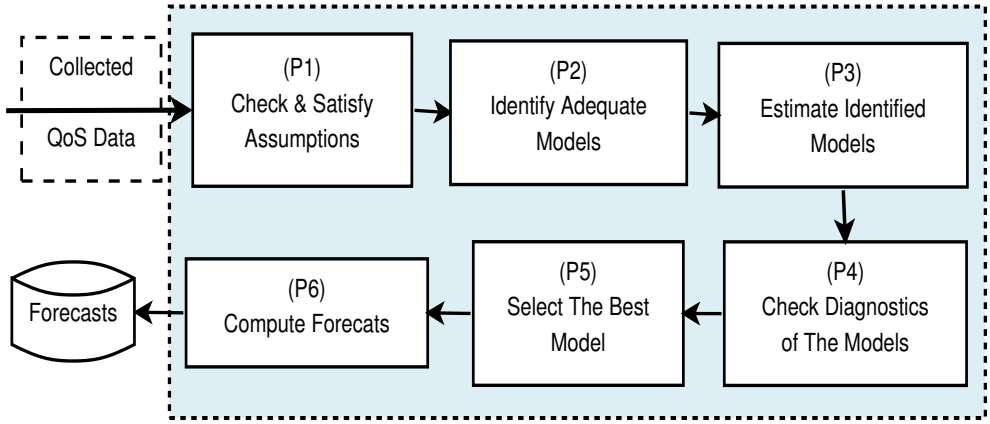


Figure 3.2: Proposed procedure for constructing adequate time series model

Regardless of the class of time series models, this procedure will be used as a base algorithm in this work to automatically construct the adequate time series model. Moreover, it is worth mentioning that more phases can be added to this procedure

depending on the time series model under construction. For example, if the time series model requires initial values for specific parameters before the estimation phase, a new phase before the estimation phase could be added to specify the initial values for those parameters. In other words, the proposed procedure can be adopted with some modifications to the given time series model based on its assumptions and requirements.

3.2.4 Evaluating Adequacy and Forecasting Accuracy

The stochastic characteristics of the given QoS data change over time, which implies that the adequacy and forecasting accuracy of the constructed time series model need to be continuously evaluated at runtime in order to enable accurate QoS forecasting. Statistically, the predictive residuals of an adequate time series model should fluctuate around zero, and recent changes in the underlying QoS data will be immediately reflected in these predictive residuals by introducing a positive or negative drift. Therefore, the adequacy of the constructed time series model can be continuously evaluated by monitoring the predictive residuals and detecting changes in their level.

In statistics literature, statistical control charts are considered as an efficient technique for online monitoring and detecting changes in a given process [78,95,157, 220]. The main idea of these control charts is constructing a center line (CL), which represents the average value of the quality characteristic, and two other horizontal lines called the upper control limit (UCL) and the lower control limit (LCL). These control limits are chosen so that if the process is in-control, which means there is no change or shift in the process, nearly all of the values will fall between them. However, a value that falls outside of the control limits is taken as a signal that a change has occurred, the process is out-of-control, and investigation and corrective action are required.

In particular, researchers [95, 157] report that the cumulative sum (or CUSUM) control charts proposed originally by Page [174] are more effective than other existing charts, *e.g.* Shewhart charts [210], for quickly detecting small process changes.

Furthermore, CUSUM are good candidate for situations where an automatic measurement is economically feasible [95]. Therefore, this research project will adopt the CUSUM chart to continuously monitor the predictive residuals of the constructed time series model in order to constantly evaluate its adequacy.

Regarding evaluating the forecasting accuracy, there are several accuracy metrics that can be used, which are summarised in the following.

- Mean squared error: Suppose the time series model is fitted to a QoS data of size n observations, y_t; and the predicted values, $\hat{y}_t$, have been obtained. Mean squared error (MSE) can be computed as follows:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}[y_t - \hat{y}_t]^2 \tag{3.1}$$

  In order to ease the comparison, MSE can be normalized by the deviation from the average of past values, *i.e.* $[y_t - \bar{y}]$ and $\bar{y}$ is the average of past values. Therefore, relative squared error (RSE) can be computed as follows:

$$RSE = \sum_{t=1}^{n}\frac{[y_t - \hat{y}_t]^2}{[y_t - \bar{y}]^2} \tag{3.2}$$

- Root mean squared error: As the unit of the MSE metric is the squared unit of the original QoS data, root mean squared error (RMSE) can be obtained to have the same unit of the original QoS data as follows:

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}[y_t - \hat{y}_t]^2} \tag{3.3}$$

  Similarly to MSE, Relative root squared error (RRSE) can be computed as follows:

$$RRSE = \sqrt{RSE} = \sqrt{\sum_{t=1}^{n}\frac{[y_t - \hat{y}_t]^2}{[y_t - \bar{y}]^2}} \tag{3.4}$$

- Mean absolute deviation (or mean absolute error): Since MSE and RMSE metrics are sensitive to outliers, mean absolute deviation (MAD) metric is proposed to be more robust against outliers, which is computed by taking the average of the absolute errors values as follows:

$$MAD = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t| \tag{3.5}$$

  Moreover, relative absolute deviation (RAD) can be computed as follows:

$$RAD = \sum_{t=1}^{n}\left|\frac{[y_t - \hat{y}_t]}{[y_t - \bar{y}]}\right| \tag{3.6}$$

- Mean absolute percentage error: Partially similarly to RAD, mean absolute percentage error (MAPE) is computed as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{[y_t - \hat{y}_t]}{y_t}\right| \times 100 \tag{3.7}$$

It should be noted that smaller values for these metrics indicate better forecasting accuracy. However, researchers [158, 175] report that the MAPE metric is easier to understand than the other metrics. This is especially the case for non-statisticians, since it is expressed as a percentage. Therefore, this research project uses the MAPE metric to continuously evaluate the forecasting accuracy of the constructed time series model.

Once the CUSUM control chart signals that the used time series model is not adequate any more for the underlying QoS data or the forecasting accuracy is very low based on the MAPE value, it becomes necessary to re-identify and re-construct other adequate time series model in order to provide a continuously accurate QoS forecasting. This construction of new adequate time series model is based on the new collected QoS data and the information obtained from the predictive residuals analysis.

3.2.5 Expected Outcome of Addressing Research Questions

The expected outcome of addressing the aforementioned research questions will be a collection of QoS characteristic-specific automated forecasting approaches that used together will be able to fit different dynamic behaviors of QoS attributes and forecast their future values. In other words, each one of these forecasting approaches will be expected to be able to fit only a specific type of stochastic characteristics of QoS attributes out of the four combinations mentioned above in Section 3.2.2. For example, one approach will be for fitting and forecasting nonlinearly dependent QoS attributes and another for fitting and forecasting linearly dependent QoS attributes with volatility clustering. Consequently, this set of forecasting approaches will constitute a general automated forecasting approach for QoS attributes.

3.3 Evaluation Strategy

Various accuracy and performance aspects of the proposed forecasting approaches need to be investigated and evaluated. To achieve this, the forecasting approaches will be applied to various QoS datasets of real-world Web services belonging to different applications and domains. These real-world QoS datasets will be collected as discussed and planned in Section 3.2.1.

More specifically, the accuracy of the proposed forecasting approaches can be classified into two types: (1) The accuracy of forecasting QoS values, and (2) The accuracy of forecasting potential violations of QoS requirements. First, the accuracy of forecasting QoS values can be measured by the MAPE metric, as discussed in the previous section. On the other hand, the accuracy of forecasting potential QoS violations can be measured and evaluated by proposing *contingency table-based metrics*. Before introducing these metrics, it is worth mentioning that the contingency table has four cases which are the basis for the proposed metrics. These cases are:

- True positive (TP): A violation was forecasted, and an actual violation occurred.

- False positive (FP): A violation was forecasted, but no actual violation occurred.
- True negative (TN): A non-violation was forecasted, and no actual violation occurred.
- False negative (FN): A non-violation was forecasted, but an actual violation occurred.

Based on these cases, contingency table-based metrics [147, 148, 199] can be defined and computed as follows:

- Precision value (PV): Is the percentage of correctly forecasted violations to total forecasted violations, which is computed as follows:

$$PV = \frac{TP}{TP + FP} \times 100 \tag{3.8}$$

- Recall value (RV): Is the percentage of correctly forecasted violations to total actual violations, which is computed as follows:

$$RV = \frac{TP}{TP + FN} \times 100 \tag{3.9}$$

- False positive rate (FPR): Is the percentage of incorrectly forecasted violations to the number of all non-violations, which is computed as follows:

$$FPR = \frac{FP}{FP + TN} \times 100 \tag{3.10}$$

- Negative predictive value (NPV): Is the percentage of correctly forecasted non-violations to total forecasted non-violations, which is computed as follows:

$$NPV = \frac{TN}{TN + FN} \times 100 \tag{3.11}$$

- Specificity value (SV): Is the percentage of correctly forecasted non-violations

to total actual non-violations, which is computed as follows:

$$SV = \frac{TN}{TN + FP} \times 100 \tag{3.12}$$

- F-measure value (FMV): Is the weighted harmonic mean of precision value (PV) and recall value (PV), which is computed as follows:

$$FMV = \frac{(1 + \beta^2) \cdot PV \cdot RV}{\beta^2 \cdot PV + RV}, \tag{3.13}$$

  where $\beta \geq 0$ is the weighted parameter.
- Accuracy value (AV)[1]: Is the percentage of all correctly forecasted violations and non-violations to the number of all forecasted violations and non-violations, which is computed as follows:

$$AV = \frac{TP + TN}{TP + FP + TN + FN} \times 100 \tag{3.14}$$

By relating these metrics to the adaptation of Web services or service-based systems which is discussed in Chapter 2, precision value can be used to evaluate incorrectly forecasted needs for adaptation, *i.e.* unnecessary adaptations [148]. Accordingly, a higher precision value means fewer false alarms of violations and thus implies less unnecessary adaptations. Similarly, recall value can be related to missed adaptations, where higher values means more actual violations being forecasted and thus implies fewer missed adaptations [148]. Consequently, the proposed forecasting approaches should achieve high values of precision and recall. However, researchers [134, 148, 199] report a trade-off between precision and recall to the extent that improving precision, *i.e.* reducing the number of false positives, might result in worse recall, *i.e.* increasing the number of false negatives. In order to consider the trade-off between precision and recall in one metric, the F-measure value has been proposed as a weighted harmonic mean of precision and recall [125, 134, 199, 245].

[1] As a note on terminology, "accuracy" is used as a generic term in this thesis as long as it is not referred explicitly as a contingency table-based metric.

Indeed, the F-measure value is balanced when the weighted parameter $\beta = 1$, and otherwise it favors precision when $\beta < 1$ and recall when $\beta > 1$ [148].

Similarly to the use of recall value, the negative predictive value can be used to evaluate missed adaptations, because a higher value of the negative predictive value means more actual violations being forecasted and thus implies fewer missed adaptations [147, 148]. Additionally, similar to the precision value, specificity value can be related to unnecessary adaptations, and a higher value of specificity means less false alarms of violations and thus implies fewer unnecessary adaptations [147, 148]. Finally, accuracy value takes into account all the cases of violations and non-violations, which can be used as a general metric for the accuracy of forecasting QoS violations. However, Salfner *et al.* [199] do not recommend using this metric as a sole indicator for evaluating the accuracy of forecasting QoS violations. Salfner *et al.*'s justification is that the forecasting approach can achieve a higher accuracy value despite it might not catch any actual violation, because the failures or violations are usually rare events. Moreover, Metzger *et al.* [148] point out that in the case of service-based systems the majority of QoS observations will indicate non-violations, and as a result the negative predictive value, specificity, and accuracy metrics might always be high. This is why the precision and recall metrics (or, as a single metric, F-measure value) is sufficient to evaluate the forecasting accuracy of these QoS datasets.

Based on this discussion of the introduced metrics and their relation to the adaptation of service-based systems, it can be concluded that metrics that relate to unnecessary adaptations or missed adaptations and cover all the four cases of the contingency table should be considered in order to achieve a comprehensive picture of evaluating forecasting accuracy [147, 148]. Therefore, this research project will consider the negative predictive value, specificity, F-measure value, and accuracy metrics to evaluate the accuracy of forecasting QoS violations because they relate to unnecessary adaptations and missed adaptations as well as cover all those four cases of the contingency table.

Regarding the performance of the proposed forecasting approaches, it can be simply measured in two ways, namely the time required to *construct* the time series model and the time taken to *use* the time series model. These times may be quite different. In addition, the time series model may only need to be constructed occasionally, whereas it will be continuously used. Obviously, the less time required to construct or use the time series model the higher performance the forecasting approach achieves. The accuracy and performance of the proposed forecasting approaches will be compared to those of the baseline ARIMA models in order to evaluate the extent of any relative improvement of those proposed forecasting approaches. In addition, non-parametric tests will be used to evaluate the significance of any difference in accuracy or performance.

3.4 Summary

This chapter first presented the challenges, formulated as research questions, of developing a general automated forecasting approach for QoS attributes. These challenges include evaluating the QoS stochastic characteristics, specifying the class of adequate time series models, constructing the specified time series models, and finally evaluating the adequacy and accuracy of the constructed time series model. The chapter then introduced the research approach that will be applied to address these formulated research questions, aiming to achieve the overall research goal. Finally, it discussed the evaluation strategy that will be used to evaluate the accuracy and performance of the contributions in this thesis.

Chapter 4

Evaluation of Stochastic Characteristics of QoS Attributes

In order to propose an efficient forecasting approach that is able to adequately fit a dynamic behavior of QoS attributes and accurately forecast their future values, it is required in the beginning to identify and evaluate the stochastic characteristics of these QoS attributes. This is because the proposed forecasting approach has to be constructed based on the QoS stochastic characteristics. As discussed in Chapter 3, these QoS stochastic characteristics include probability distribution, serial dependency, stationarity (in the mean and variance), and nonlinearity.

The evaluation of these stochastic characteristics has to be based on real-world QoS datasets to represent real characteristics. However, as mentioned in Chapter 3, there is a lack of existing real-world QoS datasets that can be used to evaluate the QoS stochastic characteristics, and then enable the construction of adequate QoS forecasting approach. In order to address this problem and achieve the current research goal, several real-world Web services are invoked, and their response time and time between failures are computed.

This chapter is organized as follows. Section 1 explains how the real-world Web services are invoked, and how their response time and time between failures datasets are computed. After that, Section 2 introduces each QoS stochastic characteristic,

followed by a discussion of how it can be evaluated using statistical tests/methods. This is achieved along with a running example of evaluating the stochastic characteristics of response time and time between failures of real-world Web service in order to explain how the evaluation is conducted. Finally, Section 3 discusses the results of evaluating stochastic characteristics of the collected response time and time between failures datasets.

4.1 Invocation of Real-World Web Services

Real-world Web services can be monitored from server-side and client-side as discussed in Chapter 2. Although server-side monitoring might provide accurate QoS measures, it requires access to the actual service implementation which is not always possible [153]. In contrast, client-side monitoring is independent of the service implementation; however, the collected QoS measures might be affected by different uncontrolled factors such as networking performance. Because in this thesis several real-world Web services are planned to be invoked and the access to their actual implementation is difficult, the client-side invocation and monitoring approach is adopted in the current research work.

Technically, in order to invoke real-world Web services some steps have to be followed, which include discovering real-world Web services, getting their WSDL files, and finally generating client-side invocation codes. These steps are discussed in some details in the following.

Discovering Real-World Web Services

Many real-world public Web services are available on the Internet, and they can be discovered form different sources such as:

- XML-based UDDI (Universal Description, Discovery and Integration) registries, which enable companies to publish and crawl public web services on the Internet.

- Web service search engines, which index public Web services and enable users to perform search queries to find them. Examples of these search engines are seekda.com, esynaps.com and cowebservices.com.
- Web service portals such as remotemethods.com, wsindex.org, xmethods.net, and webservicelist.com.

Currently, based on seekda.com counter report [207], there are totally 28,606 real-world Web services which are publicly available on the Internet with WSDL documentations.

Getting Web Services WSDL Files and Generating Invocation Codes

To get the Web services WSDL files, it is required to establish HTTP connections to the WSDL addresses. Once these HTTP connections are successfully established without failures, WSDL files can be downloaded. Using the obtained WSDL files, Axis2[2] can be employed to generate client-side invocation codes for those available Web services.

Collected Response Time and Time Between Failures Datasets

With the assistance of the tool Ws-dream [256], 800 real-world Web services have been selected randomly, without any personal selection judgment. Then, each one of these Web services has been invoked sequentially for about 1,000 times and its non-functional performance has been recorded, which includes response time, response data size, response HTTP code, and failure message. The response time is computed by measuring the time taken between sending a request to a service and receiving a response. In the current case of invoking real-world Web services, the response time is assumed to be independent of the input data values.

Using the Web service response HTTP codes, it can be detected whether the Web service invocation has succeeded or failed; and if it fails, what is the failure

[2] `http://ws.apache.org/axis2`

type. Generally, HTTP code 200 reports that the invocation is successful, which means that the request is processed under stated conditions and the response is received in a specified time interval [116]. However, other codes (and exceptions) indicate to several types of Web service invocation failures [256]. These types of invocation failures are presented in Table 4.1, and discussed briefly in the following:

- Bad Request: The HTTP protocol is not completely respected by the client request which causes that the Web server is confused and unable to fully understand the request.
- Internal Server Error: An unexpected condition is encountered by the Web server, which prevents fulfilling correctly the client request.
- Bad Gateway: An invalid response from an upstream server is received by a gateway or proxy server.
- Service Unavailable: Because of a temporary maintenance or overloading of the Web server, the HTTP request is not handled and processed by the service.
- Unknown Host: The host's IP address can not be determined.
- Connection Refused: While a socket attempts to connect to a remote address, an error occurs. This means the connection is remotely refused.
- Connection Reset: A socket is unexpectedly closed from the server-side.
- Connect Timed Out: A timeout occurs on a socket connect.
- Read Timed Out: A timeout occurs on a socket read.

These failures are caused by different Web service invocation errors which can be classified as:

- Server-side errors
- Network connection problems
- Socket exceptions

Failure Message	Description
java.io.IOException: Server returned HTTP response code: 400 for URL	Bad request
java.io.IOException: Server returned HTTP response code: 500 for URL	Internal server error
java.io.IOException: Server returned HTTP response code: 502 for URL	Bad gateway
java.io.IOException: Server returned HTTP response code: 503 for URL	Service is unavailable
java.net.UnknownHostException	Unknown host
java.net.ConnectException: Connection refused	Connection refused
java.net.SocketException: Connection reset	Connection reset
java.net.SocketTimeoutException: connect timed out	connect timed out
java.net.SocketTimeoutException: Read timed out	Read timed out

Table 4.1: Failure types of Web services invocations

The failures that are caused by the server-side errors include bad request, internal server error, service unavailable, connection reset, and connection refused. In addition, network connection problems cause other failures such as bad gateway and unknown host. Besides all these failures, timeout failures, which include connect time out and read time out, are caused by socket exceptions during socket connection and socket read respectively. It is worth mentioning that, in this work the Web service invocations have been configured with a default timeout setting of Axis2, which is 20 seconds. Of course, by setting different timeout value the number of timeout failures may vary.

Indeed, 1,000 invocations of a Web service can not guarantee getting enough number of failures that can be used to compute time between failures datasets. Therefore, 325 Web services out of the 800 real-world Web services have been selected to be invoked every 10 minutes for 150 days. The main criterion of selecting these Web services is that they are mostly used in practice according to seekda.com evaluation. The description of a sample of these selected Web services is reported in Table 4.2, and more details are introduced in Appendix A. It is important to note that the time between invocations is selected to be 10 minutes only to help collecting enough number of failures and does not have any effect on the response time. Indeed, the Web service's response time level from the client's point of view is made

up of many aspects such as network performance, current load from other clients, complexity of data requests, and load of the server from other Web services. Using the failures data obtained from this long time-based invocation, the time between failures datasets have been computed without taking into account the distinction between the failures types presented in Table 4.1. Thus, the current research considers the computed response time and time between failures datasets as the main QoS measures that are used in this thesis to evaluate the QoS stochastic characteristics of Web services, and then used in proposing and evaluating an automated forecasting approach for QoS attributes.

4.2 QoS Stochastic Characteristics and How to Evaluate

This section introduces the key QoS stochastic characteristics, which include probability distribution, serial dependency, stationarity, and nonlinearity, and discusses how to evaluate each one using statistical methods/tests. In the beginning, it introduces the fitting of probability distributions to QoS datasets using the maximum likelihood estimation method [4, 38] and how to achieve normality using the power transformation method [32]. Then, the section discusses the QoS serial dependency and how it can be evaluated using the runs test [233]. After that, it introduces the QoS stationarity concept, which is differentiated into two types; stationarity in the mean and stationarity in the variance. It then discusses how these two types of stationarity can be evaluated using the KPSS test [115] and Engle test [115], respectively. Finally, the section introduces the QoS nonlinearity and how it can be evaluated using the Hansen test [90]. This is achieved along with evaluating the stochastic characteristics in detail on the running example of the response time and time between failures datasets of "GlobalWeather"[3] service. This Web service provides the current weather with additional information for major cities around

[3] `http://www.webservicex.com/globalweather.asmx`

WS_{id}	WS Name	Description	Provider Name
WS_1	StockQuote	Reports stock quotations for a company by using provided stock symbol.	WebserviceX.NET
WS_2	YahooQuoteWebService	Gets delayed stock information from Yahoo by using provided stock symbol.	datasprings.com
WS_3	HolidayService	Calculates national holidays for the provided country code.	holidaywebservice.com
WS_4	PhoneNotify	Delivers on-demand voice notifications, including alerts and two-way interactive voice messaging.	CDYNE Corporation
WS_5	GetAuditInfo	Gets some infromation about executing an operation of a system as well as users information such as user, name, password, date, and time.	topfo.com
WS_6	SmsSend2	Sends two-way SMS messages.	utnet.cn
WS_7	Research	Research service in Microsoft Office 2003 provides a definition, a synonym, facts about a company's finances, an encyclopedia article, or other types of information from the Web.	microsoft.com
WS_8	TiempoService	Used by transportesjoselito.com to get the time.	transportesjoselito.com
WS_9	Doc	Used by shuaiche.com to implement a set of document style interop operations.	shuaiche.com
WS_{10}	Service1	Used by visualprog.cz as authentication service in order to allow clients to get a globally unique identifier (GUID) from the database by using their login names and passwords.	visualprog.cz
WS_{11}	AjaxWS	Used by cnblogs.com to collect users comments and questions.	cnblogs.com
WS_{12}	BookStoreService	Provides the list of the books according to author, title, price and chckes for their availability.	tempuri.org
WS_{13}	ValidateCodeWS	Supports codes validation including Chinese letters, numbers, images and multimedia.	webxml.com.cn
WS_{14}	TraditionalSimplifiedWS	Provides conversion of simplified Chinese from/to traditional Chinese.	webxml.com.cn
WS_{15}	SharepointEmailWS	Is sharepoint email integration Web service that creates, modefies, and deletes contacts and groups details.	perihel.hr

Table 4.2: Examples of the monitored real-world Web services

the world.

4.2.1 Probability Distribution and Transformation to Normality

Although it is known that QoS attributes are probabilistic and can be characterized by specific probability distributions such as gamma and weibull distributions [25,151, 205], it is required to evaluate these distributions based on real-world QoS datasets. This evaluation of QoS probability distributions is important to guide in selecting the suitable statistical method/test to study and analyze the given QoS attributes, such as proposing a forecasting model to fit response time measures and forecast their future values. Consequently, one of the current research tasks is to evaluate the probability distributions of QoS attributes, especially response time and time between failures.

Generally, there are different techniques for fitting probability distribution such as the maximum likelihood estimation method [4,38], least square estimation method [185], method of L-moments [101], and method of moments [61]. However, the maximum likelihood estimation method is the most commonly used because of the general good properties of its estimates such as unbiasedness, consistency, efficiency, and sufficiency [76]. Therefore, this research project adopts this estimation method for fitting the probability distribution of QoS attributes.

For explanation, the likelihood is the probability of the data point, y_t, under the hypothesis that the data have a specific probability distribution. For a set of N points $\{y_t\}$ which are obtained from a common distribution, the likelihood function can be written as:

$$L(\{y_t\};\beta) \quad = \quad P(y_1;\beta)P(y_2;\beta)\ldots P(y_N;\beta) = \prod_{t=1}^{N} P(y_t;\beta) \tag{4.1}$$

where β is a vector of parameters of the probability distribution. By maximizing the likelihood function with respect to the distribution parameters, β, the maximum

likelihood solution is obtained. In practice, it is usually easy to maximize the log likelihood function, rather than the likelihood function itself, which converts the product in equation 4.1 into a sum as follows:

$$lnL(\{y_t\};\beta) \quad = \quad ln\prod_{t=1}^{N} P(y_t;\beta) = \sum_{t=1}^{N} lnP(y_t;\beta) \tag{4.2}$$

Assuming that $\hat{\beta}$ is the parameters' estimate that maximizes the log-likelihood function, then $\hat{\beta}$ is called the *maximum likelihood estimate* and $lnL(\{y_t\};\hat{\beta})$ is called the maximized log-likelihood function.

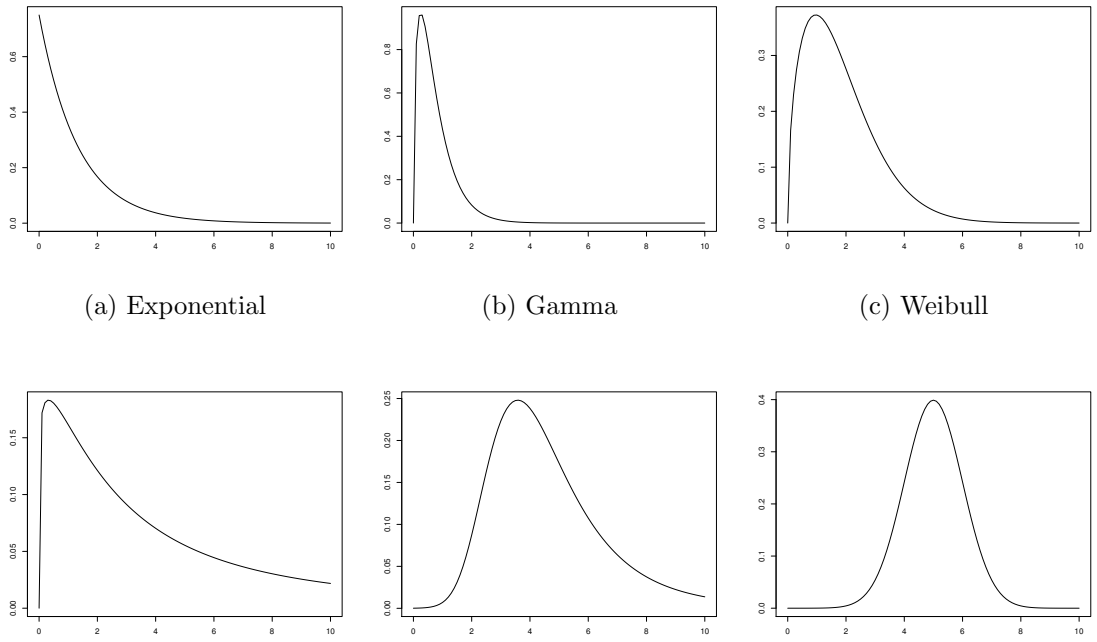
The planned method for fitting the probability distributions consists of two steps.

- First, a number of probability distributions for the given QoS data is fitted using the maximum likelihood estimation method (MLE).
- Then, the adequate distribution, which is well fitting the QoS data, is selected using Akaike's information criterion (AIC) [1]:

$$AIC \quad = \quad 2k - 2ln(L) \tag{4.3}$$

  where k is the number of parameters in the fitted distribution, and $ln(L)$ is the maximized log-likelihood function for the fitted distribution. The best adequate distribution for the given QoS data is the one that has the minimum AIC value.

As discussed in Chapter 3, because response time and time between failures datasets are theoretically asymmetrically distributed [25, 151, 192, 205], the probability distributions considered in the current evaluation are skewed distributions which include exponential, gamma, weibull, log-logistic, and non-central student's t (or simply non-central t). In addition, to check whether a symmetric distribution can characterize these QoS attributes, the normal distribution is added in the evaluation to all be six fitted probability distributions. Examples of these distributions are depicted in Figure 4.1.



(a) Exponential (b) Gamma (c) Weibull

(d) Log-logistic (e) Non-Central t (f) Normal

Figure 4.1: Examples of fitted probability distributions

Most of the powerful (parametric) statistical tests, methods, and models assume that the data is normally distributed. This assumption is reasonable in the cases where the data observations follow the normal distribution. However, in the current case, the QoS attributes, namely response time and time between failures, are expected to be mostly asymmetrically and non-normally distributed. Therefore, it is required to modify (statistically called "transform") the QoS data to be normally (or at least approximately normally) distributed to make the using of those statistical methods based on normal assumption more appropriate. Power transformation, especially Box-Cox transformation [32], is the most commonly used technique to transform the data to be normally distributed. By way of explanation, the Box-Cox transformation $y_{t(\lambda)}$ of the data z_t is given as follows:

$$y_{t(\lambda)} = \begin{cases} \frac{(z_t^{\lambda}-1)}{\lambda} & \text{if } \lambda \neq 0 \\ \log z_t & \text{if } \lambda = 0 \end{cases} \tag{4.4}$$

where λ is the transformation parameter and its value is chosen to reduce the variation of the data z_t in order to achieve normality.

In this work, because forecasting approaches are proposed based on time series models that assume normality, the Box-Cox transformation is applied to transform the response time and time between failures data to be normally distributed. Moreover, it is worth mentioning that the anti-transformation can be applied to get the original data from the transformed one. For instance, assume the log transformation is used to transform the response time data to be normally distributed, and thus the forecasting model is applied to the transformed response time to forecast future values. The forecasting of original response time can be obtained by applying exponential transformation for the forecasted log response time values.

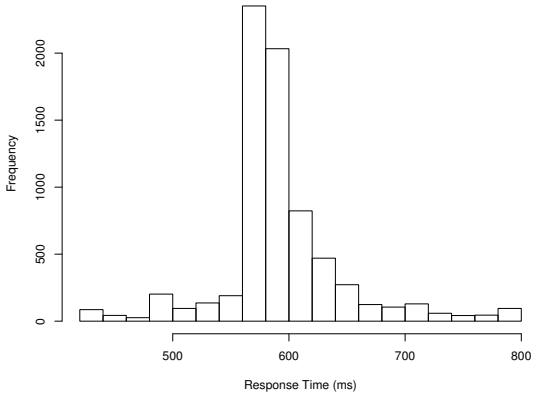
Example ▷ Initially, the descriptive statistics of the response time and time between failures of the "GlobalWeather" service are presented in Table 4.3. From this Table, it can be seen that the "GlobalWeather" service can respond on average in 583.5 ms with standard deviation is about 51 ms. Based on the first and third quartiles values ($Q1$ and $Q3$), the service's response time is between 563 ms and 594 ms in 50% of the invocations. It is worth noting that the mean of response time (= 583.5) is greater than the median (= 579.0) because the response time data is (positively) skewedly distributed. This fact is visualized by the histogram depicted in Figure 4.2a.

QoS	Min	Q1	Median	Mean	St.D.	Q3	Max
RT (ms)	437.0	563.0	579.0	583.5	51.1	594.0	797.0
TBF (min)	20.0	220.0	480.0	557.0	455.0	730.0	2010.0

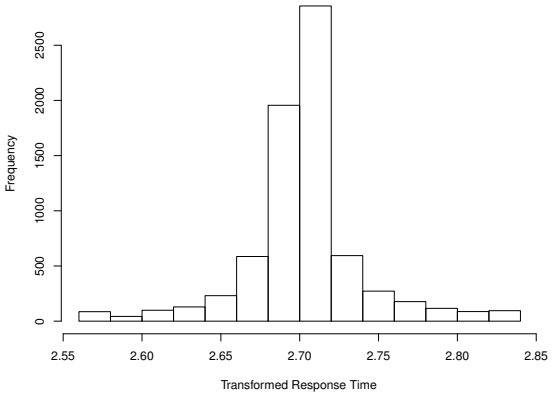
Table 4.3: Descriptive statistics of response time (RT) and time between failures (TBF) of GlobalWeather service

Regarding the time between failures measure of the "GlobalWeather" service, Table 4.3 shows that the mean time between failures (MTBF) is 557 minutes (for request rate is one request per 10 minutes), which implies that the service reliability

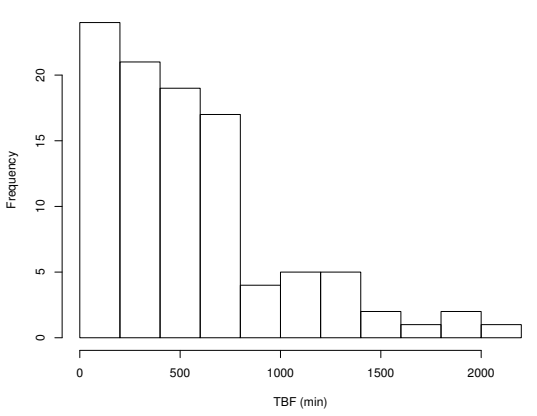
is on average about 98.2%. In addition, values of the $Q1$ and $Q3$ report that 50% of the time between failures are between 220 minutes and 730 minutes, which indicates that the time between failures is highly dynamic. Moreover, the large difference between the mean and median values implies that the time between failures measure is very (positively) skewedly distributed, as depicted in Figure 4.2c.



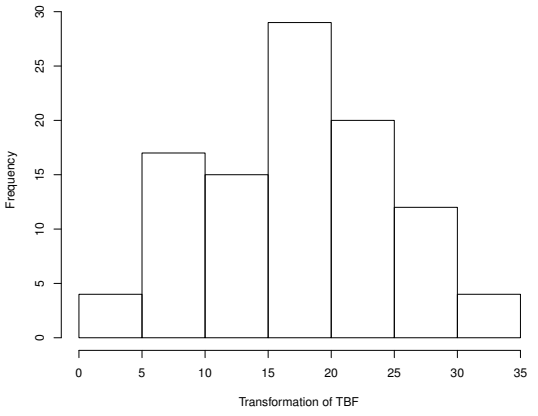
(a) Response Time (ms)



(b) Transformed Response Time



(c) TBF (min)



(d) Transformed TBF

Figure 4.2: Histograms of response time, time between failures (TBF), and their transformations of GlobalWeather service

To fit the six probability distributions for the response time and time between failures data of the GlobalWeather service, first the MLE method is used to fit the distributions, and then the AIC measure is used to select the most adequate

one. From Table 4.4, it can be seen that the most adequate distribution to fit the GlobalWeather's response time is non-central t, which has the minimum AIC value. On the other hand, the time between failures data can be well fitted by weibull distribution. However, it is worth noting that the maximized log-likelihood function and AIC values of the fitted three distributions exponential, gamma, and weibull are very similar, which means that in some cases more than one distribution can be used to fit the same QoS data. Actually, this is driven from the statistical fact that for specific values of the different distributions' parameters, these distributions can be equivalent [113].

QoS	Fitting Measure	Probability Distribution					
		Exponential	Gamma	Weibull	Log-logistic	Non-central t	Normal
RT	MLL	-7368.99	-5347.61	-5492.27	-5441.75	*-5174.28*	-5353.07
	AIC	14739.98	10699.23	10988.55	10889.49	*10354.55*	10710.14
TBF	MLL	-507.02	-505.65	*-505.14*	-515.03	-525.85	-528.40
	AIC	1016.05	1015.30	*1014.27*	1034.06	1057.69	1060.80

Table 4.4: Maximized log-likelihood (MLL) and AIC values of fitting probability distributions

Visualization can be used as a simple method to illustrate the fitting results. For example, by comparing the histograms of response time (in Figure 4.2a) and time between failures data (in Figure 4.2c) to the simulated examples of non-central t (in Figure 4.1e) and Weibull distributions (in Figure 4.1c), respectively, it can be seen that their shapes are similar.

Now based on the fitting results, the GlobalWeather's response time and time between failures datasets are not normally distributed; and to apply the statistical methods which assume normality to analyze these datasets, the Box-Cox transformation can be used to transform them to be normally distributed. By applying the Box-Cox transformation to the response time data, it is reported that the transformation parameter of value "0.156" transforms the data to be (approximately) normally distributed as depicted in Figure 4.2b. On the other hand, time between

failures is transformed to be (approximately) normally distributed by using transformation parameter of value "0.467", as presented in Figure 4.2d. ◁

4.2.2 Serial Dependency

In order for QoS data to be effectively characterized and forecasted by using time series models, it should be serially dependent (autocorrelated over time). This is why serial dependency characteristic is very important and needs to be evaluated in the early phase of time series modeling before doing any further data analysis to decide whether those time series models are suitable to fit QoS data and accurately forecast future values. There are several well-known statistical tests proposed by Wald and Wolfowitz [233], Wald and Wolfowitz [234], Moore and Wallis [160], Mann [142], Daniels [56], and Foster and Stuart [71] to evaluate the serial dependency. The test proposed by Wald and Wolfowitz [233] is known as the runs test, and it is studied by David [58], Goodman [81], and Granger [83]. In particular, Granger [83] concludes that the runs test is both much quicker to apply than other available tests and appropriate for use with non-stationary data. Therefore, this test is adopted in this work for evaluating the serial dependency of QoS attributes.

The runs test [77, 233] is used to test the null hypothesis that the elements of the QoS time series are mutually independent. If this hypothesis is rejected that means the given QoS data is serially dependent, and time series modeling can be used to construct a forecasting model for this data. In order to explain how the runs test works to evaluate the QoS serial dependency, assume there are N observations of the QoS data, $\{y_t\}$ for t = (1, . . . , N), and their median is computed; then the test compares each observation to the median value and creates a random variable of symbols takes values positive (+) or negative (-) according to whether the observation is larger or smaller than the median value. After that, the test defines the run as a sequence of identical symbols. The number of runs provides information that can be used to check whether QoS data is serially dependent; where if there are few runs, this means the QoS data is most likely dependent and otherwise it is

random and independent. Assuming the number of runs is a random variable, R, with mean and variance can be calculated as follows:

$$E(R) = (\frac{2N_1N_2}{N}) + 1, \tag{4.5}$$

$$V(R) = \frac{2N_1N_2(2N_1N_2 - N)}{N^2(N-1)} \tag{4.6}$$

where N, N_1, and N_2 are the total number of QoS observations, positive (+) runs, and negative (-) runs, respectively. Based on the calculated mean and variance, the Z statistic can be constructed to test the null hypothesis that the QoS data is independent against the alternative hypothesis that it is serially dependent, as follows:

$$Z = \frac{r + h - E(R)}{\sqrt{V(R)}} \tag{4.7}$$

where r is the total number of runs, and h equals to 0.5 if $\{(2N_1N_2 - N) + 1\}$ is greater than r and otherwise equals to -0.5. At a confidence level 95%, the hypothesis that QoS data is serially dependent is not rejected if the absolute value of Z is greater than 1.96.

Example ▷ By applying the runs test to the response time and time between failures datasets of the GlobalWeather service, the results are obtained and reported in Table 4.5. From this Table, it can be concluded that these two datasets are serially dependent, where p-values are less than 0.05. ◁

QoS	Z-Statistic	P-Value
RT	-3.6058	0.0003
TBF	-2.6994	0.0069

Table 4.5: Runs test results for the GlobalWeather's response time (RT) and time between failures (TBF)

4.2.3 Stationarity

In time series analysis, at each measurement point only one observation is observed for a variable of interest such as a response time of each service request, which constructs one realization of data. The mean, variance, and autocorrelations of the series of interest can be estimated by averaging across the single realization only if the series is stationary. This is why most time series models assume that the time series of interest is stationary or has been stationarized.

Theoretically, there are two types of stationarity; strict (or strong) stationarity and weak stationarity [33]. To explain this concept, assume the joint distribution function of the N random variables $\{Y_{t_1}, \ldots, Y_{t_N}\}$ drawn from the stochastic process $\{Y_t : t = 0, \pm 1, \pm 2, \ldots\}$ can be written as follows:

$$F_{Y_{t_1},\ldots,Y_{t_N}}(y_{t_1}, \ldots, y_{t_N}) = P\{Y_{t_1} \leq y_{t_1}, \ldots, Y_{t_N} \leq y_{t_N}\} \tag{4.8}$$

where y_{ti} for $i = 1, 2, \ldots, N$ are real numbers. A time series is strongly (or strictly) stationary if the joint distribution function is the same over time and only depends on the time difference, which means that:

$$F_{Y_{t_1},\ldots,Y_{t_N}}(y_{t_1}, \ldots, y_{t_N}) = F_{Y_{t_{1+h}},\ldots,Y_{t_{N+h}}}(y_{t_{1+h}}, \ldots, y_{t_{N+h}}) \tag{4.9}$$

where h is any real number represents the time difference. For this strictly stationary time series, the mean and variance are constants and do not depend on the time, which implies that $\mu = E(Y_t)$ and $\sigma^2 = E(Y_t - \mu)^2$. On the other hand, the correlation function depends only on the time difference, which means that $\rho(Y_{t_1}, Y_{t_2}) = \rho(Y_{t_{1+h}}, Y_{t_{2+h}})$ for any time points t_1 and t_2 and time difference h.

In practice, it is not easy to check for the strict stationarity. Therefore, the empirical time series analysis is interested into the joint moments rather than the joint distribution function, and the time series is called weakly stationary of order n if it has constant joint moments up to order n. For example, in the case of second order weak stationarity the time series has constant mean and variance, and

its autocorrelation function depends only on the time difference. Accordingly, this explains why this work checks for (weak) stationarity by only testing whether the time series has constant mean and variance over time. For simplicity, when a time series has constant mean (no trend) over time, it is called stationary in the mean; and when it has constant variance (same variation) over time, it is called stationary in the variance.

4.2.3.1 Stationarity in the Mean

Regarding stationarity in the mean, Dickey-Fuller tests [62, 63, 197] and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test [115] are the most commonly used to check for stationarity in the mean of time series [60,127,136,190]. However, some researchers [100, 115, 164] report that the Dickey-Fuller tests have low power against stationarity, *i.e.* they highly fail to accept the alternative hypothesis of stationarity for actual stationary time series, as confirmed by the findings of empirical studies [60, 164]. Because the KPSS test tackles this problem [115], it is preferred to be adopted in this research project.

The KPSS test evaluates the null hypothesis that the QoS data is stationary in the mean. To illustrate the general idea of KPSS test, let $\{y_t\}$, for t = 1, ..., N, be the observed QoS time series data for which stationarity is tested. The test decomposes this QoS series into the sum of three parts, which are:

- A random walk which is modeled as $r_t = r_{t-1} + u_t$, where u_t is normally distributed with mean equals to zero.
- A deterministic trend which is represented as βt.
- A stationary error which is referred as ε_t.

Then, it constructs a linear regression model as follows:

$$y_t = r_t + \beta t + \varepsilon_t \tag{4.10}$$

To test the stationarity, the test actually assumes the null hypothesis that $\beta = 0$. Under this null hypothesis, the KPSS test statistic can be calculated as:

$$KPSS = N^{-2} \frac{\sum_{t=1}^{N} S_t^2}{\hat{\sigma}^2(p)} \tag{4.11}$$

where N is number of observations, S_t is the sum of regression residuals (e_t's), and $\hat{\sigma}^2(p)$ is a consistent estimator of the variance of e_t's which is computed as follows:

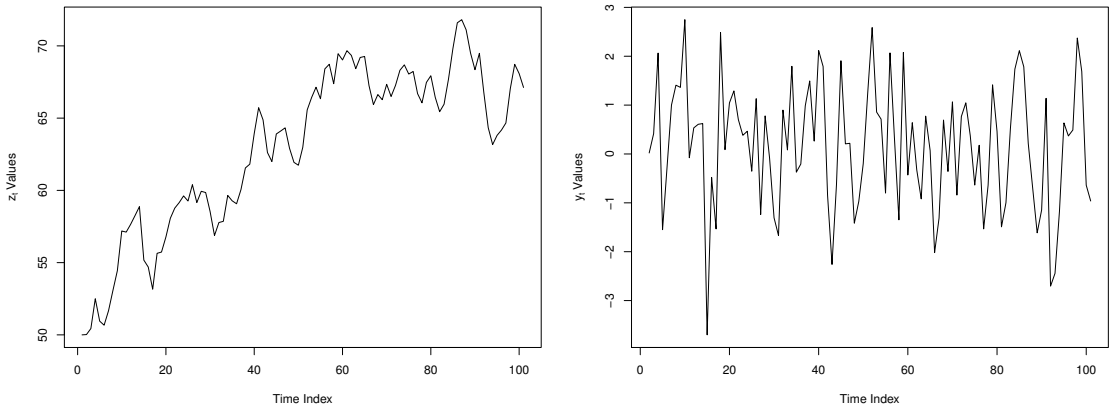
$$\hat{\sigma}^2(p) = \frac{1}{N} \sum_{t=1}^{N} e_t^2 + \frac{2}{N} \sum_{j=1}^{p} w_j(p) \sum_{t=j+1}^{N} e_t e_{t-j} \tag{4.12}$$

where $w_j(p)$ is a weighting function of the truncation lag p, such as $w_j(p) = 1 - j/(p+1)$. The decision of KPSS test is based on the upper tail critical values of the statistic's asymptotic distribution, which is given by Kwiatkowski *et al.* [115].

The rejection of KPSS null hypothesis means that the QoS data is non-stationary, and therefore a transformation method is required to stationarize this data. One of the most commonly used method to stationarize the time series data is using the differencing of the non-stationary time series. For example, let $\{z_t\}$ be the original time series which is non-stationary in the mean, has trend over time, as depicted in Figure 4.3a. It can be transformed into a stationary one $\{y_t\}$ using the first difference, *i.e.* $y_t = z_t - z_{t-1}$. The differenced series $\{y_t\}$ is depicted in Figure 4.3b, and it is clear that it is stationary in the mean.

4.2.3.2 Stationarity in the Variance

Some statistical tests are proposed by Breusch and Pagan [35], White [238], and Engle [68] in order to evaluate the stationarity in the variance. However, the Engle's test [68] is known with its simplicity [69] and efficiency especially in the availability of small number of observations [129], which is the reason to be adopted in this work. Generally, the Engle test [68] is used with the null hypothesis that the QoS data has constant variance. Technically, the Engle test in the beginning fits the



(a) The original time series $\{z_t\}$ (b) The differenced time series $\{y_t\}$

Figure 4.3: The original nonstationary vs. differenced stationary time series

most adequate autoregressive model for the QoS data $\{y_t\}$ as:

$$y_t = \phi_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t, \quad t = 1, 2, \ldots, N \tag{4.13}$$

where ϕ_i's for $i = 1, \ldots, p$ are the model coefficients and p is the model order. After fitting this model, the squared residuals $\hat{\varepsilon_t}^2$ are computed and fitted by another autoregressive model as:

$$\hat{\varepsilon_t}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \hat{\varepsilon}_{t-i}^2 + e_t, \quad t = 1, 2, \ldots, N \tag{4.14}$$

Under the null hypothesis of constant variance, it is expected that all the values of α_i's to be close to zero, which implies that the squared residuals are not auto-correlated over time. Therefore, the Engle statistic is computed as NR^2, where N is the number of QoS data observations and R^2 is the coefficient of determination in model 4.14, which measures how well the model fits the squared residuals [158]. Since this statistic asymptotically follows the $\chi^2(q)$ distribution, the decision of the test is based on the upper tail critical values of the χ^2 distribution [113]. Rejecting the Engle test's null hypothesis means that the QoS data has non-constant variance

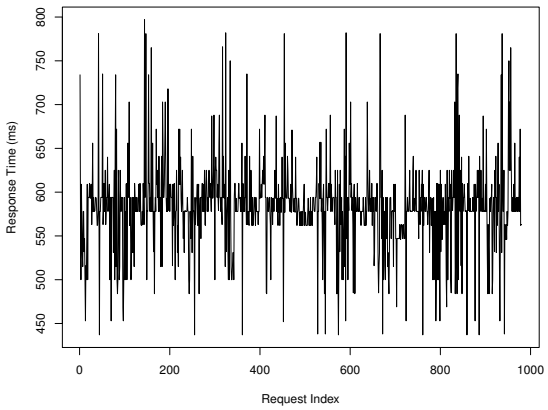
over time, which is statistically called volatility clustering (or in short volatility).

Example ▷ The stationarity in the mean of the GlobalWeather's response time and time between failures datasets is evaluated by applying the KPSS test, and the results are depicted in Table 4.6. This Table shows that both response time and time between failures datasets are non-stationary in the mean, where p-values are less than 0.05. Then, these datasets are stationarized by using the differencing method, and then the KPSS test is re-applied. The KPSS test concludes that the differences of response time and time between failures are stationary (p-values > 0.05). This result can be illustrated by Figure 4.4. By looking at Figures 4.4a and 4.4c, it can be seen that the response time and time between failures do not have constant level, where there is increasing and decreasing trend. However, Figures 4.4b and 4.4d show that the changes of response time and time between failures over time, which are computed by the differencing method, have constant level.

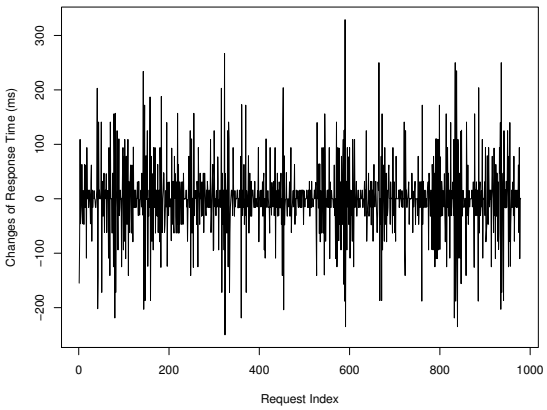
QoS	RT	D(RT)	TBF	D(TBF)
KPSS-Statistic	0.5923	0.0986	0.8769	0.1622
P-Value	0.0233	0.4251	0.0046	0.3624

Table 4.6: KPSS test results for the GlobalWeather's response time (RT), time between failures (TBF), and their differences (D(RT) and D(TBF))

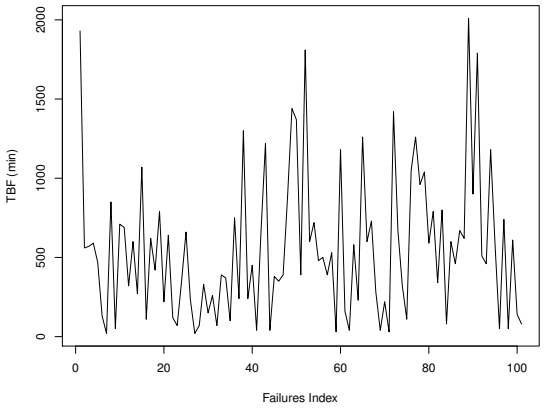
In order to evaluate the stationarity in the variance, the Engle test is applied and the results depicted in Table 4.7 show that the response time data has non-constant variance over time (p-value < 0.05) and, however, the time between failures data is stationary in the variance (p-value > 0.05). This is illustrated graphically in Figure 4.4, as it can be seen that the variation of response time is clustered over time which is clearly demonstrated by the time plot of changes in Figure 4.4b. On the other hand, the time plot of the time between failures' changes shows that its variation is approximately constant over time, as presented in Figure 4.4d. ◁



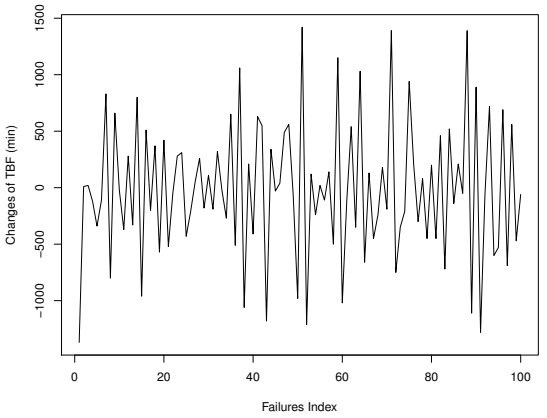
(a) Response Time (ms)



(b) Changes of Response Time (ms)



(c) TBF (min)



(d) Changes of TBF (min)

Figure 4.4: Time plots of response time, time between failures (TBF), and their changes of GlobalWeather service

QoS	Engle-Statistic	P-Value
RT	37.2506	0.0002
TBF	11.1640	0.5149

Table 4.7: Engle test results for the GlobalWeather's response time (RT) and time between failures (TBF)

4.2.4 Nonlinearity

The serially dependent QoS data can be modeled by two classes of modeling, linear and nonlinear time series modeling, based on the dynamic structure of its dependence. Linear time series modeling assumes that the QoS data $\{y_t\}$ can be modeled as a linear function of its lagged values, such as autoregressive modeling which is presented in equation 4.13. On the other hand, a nonlinear function of the lagged values is assumed by the nonlinear time series modeling to well fit the QoS data, such as exponential autoregressive model [173] which can be written as follows:

$$y_t = \sum_{i=1}^{p} \left[\alpha_i + \beta_i \exp\left(-\delta y_{t-1}^2\right)\right] y_{t-1} + \varepsilon_t \tag{4.15}$$

where α_i and β_i (for $i = 1, \ldots, p$) are the model coefficients, p is the model order, and $\delta > 0$ is a scale parameter.

Currently, various statistical tests are proposed in literature by Petruccelli and Davies [183], Tsay [230], Chan and Tong [49], and Hansen [91,92] in order to evaluate the nonlinearity. In particular, the Hansen's test [91, 92] enables analyzing the sampling distribution of the test statistic as well as deals with technical problems such as the Davies' problem [93, 109]. Therefore, the Hansen's test is recommended to be used in this research project n order to evaluate the nonlinearity of QoS attributes.

The Hansen test [90] can be used to evaluate the QoS nonlinearity by testing the null hypothesis of linearity against the nonlinearity. In particular, the Hansen test in the beginning fits an autoregressive moving average (ARMA) model [33] to the QoS data, and computes its residual sum of squares RSS_0. Then, it fits a self exciting threshold ARMA (SETARMA) model [228], which is considered as a general class of nonlinear time series models [182], and computes the residual sum of squares RSS_1. After that, the test constructs the statistic as:

$$F = \frac{RSS_0 - RSS_1}{\hat{\sigma}_1^2} \tag{4.16}$$

where $\hat{\sigma}_1^2$ is the residual variance of SETARMA model. The decision of Hansen test is based on the asymptotic distribution that is approximated by a bootstrap procedure [90]. Rejecting the null hypothesis implies that the QoS data is nonlinearly dependent and has to be modeled by a nonlinear model to get more accurate forecasts.

Example ▷ The nonlinearity of GlobalWeather's response time and time between failures datasets is evaluated by applying the Hansen test, and the results depicted in Table 4.8 show that the response time data is linearly dependent (where p-value > 0.05) and, however, the time between failures data is nonlinearly dependent (where p-value < 0.05). ◁

QoS	Hansen-Statistic	P-Value
RT	5.7741	0.7921
TBF	18.2669	0.0001

Table 4.8: Hansen test results for the GlobalWeather's response time (RT) and time between failures (TBF)

4.3 Results of Evaluating QoS Stochastic Characteristics

This section discusses in detail the results of evaluating the aforementioned stochastic characteristics of the collected response time and time between failures datasets. It then concludes with the main characteristics that have to be considered in proposing different QoS characteristic-specific forecasting approaches for QoS attributes.

■ *Fitting Probability Distribution and Transforming to Normality.* The results of fitting the probability distribution are presented in Table 4.9. This results show that most of the response time datasets are non-normally distributed ($>$ 99%), where 57.85% and 29.12% are well fitted by gamma and non-central t distributions, respec-

tively. Similarly, the time between failures datasets are non-normally distributed, and 40% and 35% of the datasets can be well fitted by weibull and exponential distributions, respectively.

Using the Box-Cox power transformation, these datasets can be transformed to be normally distributed, and the descriptive statistics of the used transformation parameter values are reported in Table 4.10. This Table illustrates that in the case of response time data the experienced parameter values are in the interval (-1.00, 1.16) with mean is "-0.135" and standard deviation is "0.525". On the other hand, in the case of time between failures data, the parameter values are in the interval (-0.12, 0.15) with mean is "-.007" and standard deviation is "0.073". This result indicates that the variation of parameter values is relatively high in the case of response time data compared to those in the case of time between failures data. Moreover, the result implies that the normality assumption can be achieved mostly using log transformation for the time between failures data, however, this is not the case for the response time data.

QoS	Probability Distribution					
	Exponential	Gamma	Weibull	Log-logistic	Non-central t	Normal
RT (%)	6.13	57.85	3.83	2.30	29.12	0.77
TBF (%)	35.00	15.00	40.00	10.00	0.00	0.00

Table 4.9: Results of fitting probability distributions for response time (RT) and time between failures (TBF)

QoS	Min	Q1	Median	Mean	St.D.	Q3	Max
RT	-1.000	-0.607	-0.049	-0.135	0.525	0.203	1.164
TBF	-0.115	-0.069	-0.019	-0.007	0.073	0.051	0.147

Table 4.10: Descriptive statistics of transformation parameter values for response time (RT) and time between failures (TBF)

■ *Serial Dependency.* The evaluation results presented in Table 4.11 indicate that

about 94.6% and 100% of the response time and time between failures datasets are serially dependent, respectively. This means that in most of the real cases, the response time and time between failures datasets are autocorrelated over time.

■ *Stationarity.* Regarding stationarity in the mean, as shown in Table 4.11, the results report that about 71.6% and 70% of the response time and time between failures datasets, respectively, are stationary and do not require any transformations or preparation activities. Of the response time datasets 21.76% and 6.68% can be transformed to be stationary using the first and the second differences, respectively. Similarly, 27.5% and 2.5% of the time between failures datasets can be transformed to be stationary using the first and the second differences, respectively. On the other hand, the results report that 30.3% and 57.5% of the response time and time between failures datasets, respectively, are stationary in the variance. This indicates that the response time datasets are more frequently nonstationary in the variance, *i.e.* volatile, than the time between failures datasets.

■ *Nonlinearity.* The evaluation results in Table 4.11 show that 26.4% and 44% of the response time and time between failures datasets, respectively, are linearly dependent. In other words, the majority of response time (*i.e.* 73.6%) and 54% of the time between failures datasets are statistically recommended to be modeled by nonlinear time series models.

		Stationarity (in)				
	Serial	Mean			Variance	Linearity
QoS	Dependency	0 Diff.	1 Diff.	2 Diffs.		
RT (%)	94.57	71.56	21.76	6.68	30.27	26.39
TBF (%)	100.00	70.00	27.50	2.50	57.50	44.00

Table 4.11: Results of evaluating key stochastic characteristics of response time (RT) and time between failures (TBF)

Results Implications

Based on the results of this empirical evaluation, it can be concluded that most of the real response time and time between failures datasets are serially dependent and can be transformed to be stationary in the mean using the differencing method, and normally distributed using the Box-Cox transformation. This implies that the time series models can be used to fit the response time and time between failures datasets and forecast their future values with some suitable transformations and preparation activities.

The results indicate that the non-stationarity in the variance (or volatility clustering) and nonlinearity are highly exhibited by the response time and time between failures qualities. For more investigation of these two characteristics, the response time and time between failures datasets are cross-tabulated by the volatility clustering and nonlinearity, and results are presented in Table 4.12. The important observation from this Table is that 54.8% and 37.5% of the response time and time between failures datasets, respectively, are both volatile and nonlinearly dependent. This result confirms that it is necessary for the current research project to propose forecasting approaches that can adequately capture the volatility clustering and nonlinearity of QoS attributes and accurately forecast their future values.

Characteristic	QoS					
	RT (%)			TBF (%)		
	Linear	Nolinear	Total	Linear	Nolinear	Total
NonVolatile	11.50	18.77	30.27	31.60	18.50	50.1
Volatile	14.89	54.84	69.73	12.40	37.50	49.9
Total	26.39	73.61	100	44.00	56.00	100

Table 4.12: Results of evaluating nonlinearity and volatility of response time (RT) and time between failures (TBF)

4.4 Summary

This chapter discussed how real-world Web services have been invoked, and how their response time and time between failures measures have been computed. It then introduced the QoS stochastic characteristics that have to be evaluated to help in proposing forecasting approaches for QoS attributes. These QoS stochastic characteristics include probability distribution, serial dependency, stationarity (in the mean and in the variance), and nonlinearity. After that, the chapter discussed the results of evaluating these stochastic characteristics of all the collected response time and time between failures datasets of the real-world Web services. The main result is that the time series models are suitable to fit the response time and time between failures and forecast their future values with some suitable transformations and data preparation activities. In conclusion, the evaluation results show that the volatility clustering and nonlinearity are two important characteristics of the response time and time between failures datasets which have to be considered while proposing QoS forecasting approaches.

Chapter 5

Forecasting Approach for Nonlinearly Dependent QoS Attributes

The objective of this chapter is to propose an automated forecasting approach for nonlinearly dependent and stationary (in the variance) QoS attributes. This is to effectively capture the nonlinearity feature of QoS attributes and provide relatively accurate QoS forecasting. In order to achieve this objective, we have reviewed the literature of nonlinear time series models and found that there are three classes of nonlinear models that can be used to fit nonlinear behavior of QoS attributes. These three classes are:

- Bilinear time series models [84, 221, 227].
- Exponential Autoregressive (EXPAR) time series models [171, 172, 173].
- Self Exciting Threshold Autoregressive Moving Average (SETARMA) time series models [225, 227, 228].

However, Petruccelli [182] has shown that the SETARMA models can be considered as a general class of nonlinear time series models, which includes exponential autoregressive models and bilinear models as special cases. Consequently, in the current work of addressing the nonlinearity of QoS attributes, the proposed forecasting ap-

proach, which is called "the forecasting approach I", is based on the SETARMA models as the main models that can fit and forecast nonlinearly dependent QoS attributes.

The main idea of the forecasting approach I is that it first constructs the best suitable SETARMA model to fit the nonlinear behavior of the underlying QoS data. After that, using the new obtained QoS data, the forecasting approach continuously updates the constructed SETARMA model, computes the QoS forecasts, and evaluates the adequacy and forecasting accuracy of the constructed SETARMA model.

In the rest of this chapter, we summarize the statistical background of the time series models and their main assumptions, then introduce the proposed forecasting approach I with a running example of response time of a real-world Web service.

5.1 Background of Time Series Models

This section introduces the background of time series models, and then discusses their main assumptions.

5.1.1 ARIMA Models

Autoregressive integrated moving average (ARIMA) models were originally proposed by Box and Jenkins [33], and they are commonly used in practice to fit linearly dependent time series data and forecast their future values. ARIMA modes have been successfully applied in a great number of fields such as financial and economic forecasting [52,189]. In addition, as reviewed in detail in Chapter 2, some researchers have applied these models to forecast future values of QoS attributes.

The time series $\{z_t\}$ is said to be generated by an autoregressive integrated moving average (ARIMA) model of orders p, d, and q, denoted by ARIMA(p,d,q), if it satisfies:

$$\phi_p(B)y_t = \theta_q(B)\varepsilon_t \tag{5.1}$$

where y_t is a stationary time series (of the original non-stationary time series $\{z_t\}$)

computed by using d differences as $y_t = (1-B)^d z_t$ and $B^d z_t = z_{t-d}$. In addition, $\{\varepsilon_t\}$ is a sequence of independent normal errors with zero mean and variance σ^2. The autoregressive polynomial is $\phi_p(B) = (1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)$ with order p and $\theta_q(B) = (1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q)$ is the moving average polynomial with order q. The autoregressive and moving average coefficients are $\phi = (\phi_1, \phi_2, \cdots, \phi_p)^T$ and $\theta = (\theta_1, \theta_2, \cdots, \theta_q)^T$ respectively. The model (5.1) can be rewritten as

$$y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{5.2}$$

where y_{t-i} for $i = 1, ..., p$ are the past stationary observations, ε_t is the current error, and ε_{t-i} for $i = 1, ..., q$ are the past errors. To forecast one-step-ahead, it is moved from (t) to (t+1):

$$y_{t+1} = \sum_{i=1}^{p} \phi_i y_{t+1-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t+1-i} + \varepsilon_{t+1} \tag{5.3}$$

and similarly it can be moved to forecast multi-step-ahead values.

It is worth mentioning that if the original time series $\{z_t\}$ is stationary, then there is no differences used and $\{z_t\}$ is said to be generated by an autoregressive moving average (ARMA) model of orders p and q and denoted by ARMA(p,q). In addition, most of the existing nonlinear time series models are normal extensions for ARIMA models including bilinear models [84], exponential autoregressive models [173], and SETARMA models [228] which are introduced in the following sections.

5.1.2 Bilinear Time Series Models

The bilinear models were introduced for the first time in the context of control theory literature in 1960s [184], then they were introduced in the statistical field by Granger and Anderson [84]. Granger and Anderson [84] studied the statistical properties of some special cases of the bilinear models, and they presented some examples of how these models arise in different fields. In addition, Tong [227] have

reported that the bilinear models are fitted for a lot of real life applications such as in ecology, solar physics, finance, geophysics and economics. Moreover, these models are further studied and analyzed by Granger and Terasvirta [85], Martins [143], Hili [99], and Malinski and Bielinska [139].

The time series $\{y_t\}$ is said to be generated by a bilinear model of orders p, q, P and Q, if it satisfies:

$$y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \sum_{i=1}^{P} \sum_{j=1}^{Q} \beta_{ij} y_{t-i} \varepsilon_{t-j} + \varepsilon_t \tag{5.4}$$

where $\{\varepsilon_t\}$ is a sequence of independent normal errors with zero mean and variance σ^2, and ϕ_i's, θ_j's, and β_{ij}'s are the unknown model parameters.

The model (5.4) is denoted by BL(p, q, P, Q) according to Subba Rao [221]. It is worth noting that the BL(p, q, P, Q) model is linear in y_t's and in ε_t's separately but not in both which gives the term bilinearity. If p and q equal to 0, the model (5.4) is called purely bilinear model, however, it is called diagonal model when $\beta_{i,j}$ $= 0$ for $i \neq j$. In addition, this model is called super diagonal when $\beta_{i,j} = 0$ for all $i > j$, and called subdiagonal when $\beta_{i,j} = 0$ for all $i < j$ [105]. Moreover, it is easy to show that the ARMA(p, q) model is a special case of the bilinear model (5.4) when β_{ij}'s equal to 0. This implies that the bilinear models are natural extensions of the ARMA models.

5.1.3 Exponential Autoregressive Time Series Models

The exponential autoregressive models were first introduced by Ozaki and Oda [173] in order to characterize specific features of nonlinear random vibration theory such as fixed points and limit cycles [146]. These models were studied in detail by Ozaki [171, 172], Shi and Aoyama [211], Shi *et al.* [212], and Baragona *et al.* [18]. The exponential autoregressive models have been used in several applications related to nonlinear dynamics, because they are able to account for amplitude-dependent frequency and jump phenomena [18]. For example, these models are used by Mes-

saoud [146] to describe the drilling torque and to characterize its time varying dynamics.

The basic idea of the exponential autoregressive models is to start with a linear autoregressive model and then allow the coefficients to be exponential functions of y_{t-1}^2 [105, 173]. Therefore, the exponential autoregressive model of order p of the time series $\{y_t\}$, denoted by EXPAR(p), can be written as follows:

$$y_t = \sum_{i=1}^{p} \left[\alpha_i + \beta_i \exp\left(-\delta y_{t-1}^2\right)\right] y_{t-i} + \varepsilon_t \tag{5.5}$$

where $\{\varepsilon_t\}$ is a sequence of independent normal errors with zero mean and variance σ^2, α_i's and β_i's are the unknown model parameters, and $\delta > 0$ is a scale parameter. The EXPAR(p) model can be extended in different ways such as allowing the coefficients to be exponential functions of y_{t-d}^2, where $d \geq 1$ is a delay parameter [105]. For more details about the extensions of the exponential autoregressive models see [171, 172, 227]. Moreover, it is worth noting that when $\delta = 0$ the EXPAR(p) collapses to become a linear autoregressive model, which is a special case of the ARMA models.

5.1.4 SETARMA Models

Self exciting threshold autoregressive moving average (SETARMA) model was first introduced by Tong and Lim [228] and further mentioned and studied in detail by Tong [225, 227], Lim [126], and Cook and Broemeling [53]. Tong [225] reports that threshold effects can arise in many scientific fields and the SETARMA models are able to characterize this because of their attractive features such as limit cycles. Consequently, the SETARMA models have been found useful in many real life applications, which include economics, population biology, hydrology, and other areas [105, 226].

The SETARMA model is a generalization of the ARMA model in the nonlinear domain, and its main idea is to start with a linear ARMA model and then allow

the parameters to vary according to the past values of the time series data [105]. In order to explain the idea, let l disjoint intervals be defined as $R_j = [r_{j-1}, r_j)$ for $j = 1, 2, \ldots, l$, and let an integer d_p be known as the delay parameter. For the time series $\{y_t\}$, each interval R_j defines a "regime", in the sense that, the time series value y_t is said to follow the regime j if $y_{t-d_p} \in R_j$ [19]. Accordingly, a SETARMA model is defined as a piecewise linear structure that follows a linear ARMA model in each j alternative regime, for $j = 1, 2, \ldots, l$, and switches among the different regimes based on the threshold values which are determined by the past values of the time series data [6].

The SETARMA model of order $(l; p_1, p_2, \cdots, p_l; q_1, q_2, \cdots, q_l)$ or SETARMA $(l; p_1, p_2, \cdots, p_l; q_1, q_2, \cdots, q_l)$ can be written as follows:

$$y_t = \mu^{(j)} + \sum_{i=1}^{p_j} \phi_i^{(j)}\ y_{t-i} + \sum_{s=0}^{q_j} \theta_s^{(j)}\ \varepsilon_{t-s} + \varepsilon_t^{(j)} \qquad if \quad r_{j-1} \leq y_{t-d_p} < r_j \tag{5.6}$$

where $\phi_i^{(j)}$ and $\theta_s^{(j)}$ $(i = 1, 2, \cdots, p_j; s = 1, 2, \cdots, q_j; j = 1, 2, \cdots, l)$ are model parameters, and $\left\{\varepsilon_t^{(j)}\right\}$ $(j = 1, 2, \cdots, l)$ are a sequence of independent normal errors with mean zero and variance σ_j^2. The ordered constants $-\infty = r_0 < r_1 < \cdots < r_l = \infty$ are known as the thresholds.

When q_j equals to zero (for $j = 1,\ 2,\ \cdots,\ l$), the SETARMA model is reduced to the self exciting threshold autoregressive model which is denoted by SETAR$(l; p_1, p_2, \cdots, p_l)$. Similarly, the self exciting threshold moving average model, SETMA$(l; q_1, q_2, \cdots, q_l)$, is a special case of SETARMA when p_j equals to zero (for $j = 1,\ 2,\ \cdots,\ l$). If the autoregressive orders and moving average orders are the same for all regimes and equal to p and q respectively, the SETARMA model (5.6) takes the form:

$$y_t = \mu^{(j)} + \sum_{i=1}^{p} \phi_i^{(j)} y_{t-i} + \sum_{s=0}^{q} \theta_s^{(j)} \varepsilon_{t-s} + \varepsilon_t^{(j)} \qquad if \quad r_{j-1} \leq y_{t-d_p} < r_j, \tag{5.7}$$

which is SETARMA(l, p, q) where p and q are repeated l times. Similarly to Bi-

linear models and exponential autoregressive models, it is easy to show that the ARMA(p, q) model is a special case of the SETARMA model (5.7) when l equals to 1, which implies that the SETARMA models are natural extensions of the ARMA models.

5.1.5 Assumptions of Time Series Models

The main assumptions of time series models are serial dependency, normality, stationarity, and invertibility [33]. These assumptions are briefly discussed in the following.

1. *Serial dependency*: In order for time series data to be effectively characterized using time series models, it should be serially dependent (autocorrelated) over time. Accordingly, this is the initial requirement needs to be evaluated for the time series models in order to effectively fit the QoS attributes and accurately forecast their future values.

2. *Normality*: Time series models assume that the given time series data is normally distributed, because all the computations of identifying, estimating, and evaluating its parameters are based on a normal distribution. In the case of non-normally distributed time series data, it can be approximated to normal distribution using power transformations [32] as discussed in Chapter 4.

3. *Stationarity*: As mentioned in Chapter 4, time series models assume that the time series data has constant mean, no trend, over time, which is referred as stationarity in the mean. However, if the original time series data is non-stationary, it can be transformed into a stationary in the mean using the differencing method.

4. *Invertibility:* Time series models that are used to forecast the future values should be invertible. This means that the error term in the time series model can be expressed as a weighted sum of current and prior observations and prior errors to enable forecasting. For more illustration, in the simple case of

time series models, MA(1), the error term can be written as: $\varepsilon_t = y_t - \theta\varepsilon_{t-1}$, and then re-written recursively to be equivalent to: $\varepsilon_t = y_t - \sum_{i=1}^{\infty} \theta^i y_{t-i}$. Obviously, this model cannot be used to forecast future errors except that ε_t has a finite value which requires that the absolute value of θ to be less than one (*i.e.* $|\theta| < 1$), and this is the invertibility concept.

Investigating whether the given time series data satisfies these assumptions is important task, because unsatisfied assumptions lead to inadequate time series models that in turn will provide inaccurate forecasts. Therefore, we carefully consider these assumptions in our proposed forecasting approaches.

5.2 Forecasting Approach I based on SETARMA Models

The proposed forecasting approach I integrates SETARMA models and some statistical tests in order to effectively capture the nonlinear dynamic behavior of QoS attributes and accurately forecast their future values and potential violations. In brief summary, using the collected QoS data the forecasting approach first constructs the best suitable SETARMA model to fit the nonlinear dynamic behavior of QoS data. Then, using the new obtained QoS data the forecasting approach continuously updates the constructed SETARMA model, computes the QoS forecasts, and evaluates the adequacy and forecasting accuracy of the constructed SETARMA model.

This approach consists of two components; one for constructing the SETARMA model and the other for continuously forecasting future QoS values and evaluating the adequacy and forecasting accuracy of the constructed SETARMA model, as explained in Figure 5.1. For more illustration of how this approach works, the functionalities of each component are introduced in detail in the following subsections with a running example of the response time dataset (which is referred as $WS_1(RT)$) of the Web service "YahooQuoteWebService". This Web service is used

by datasprings[1] to get the stock information from Yahoo.

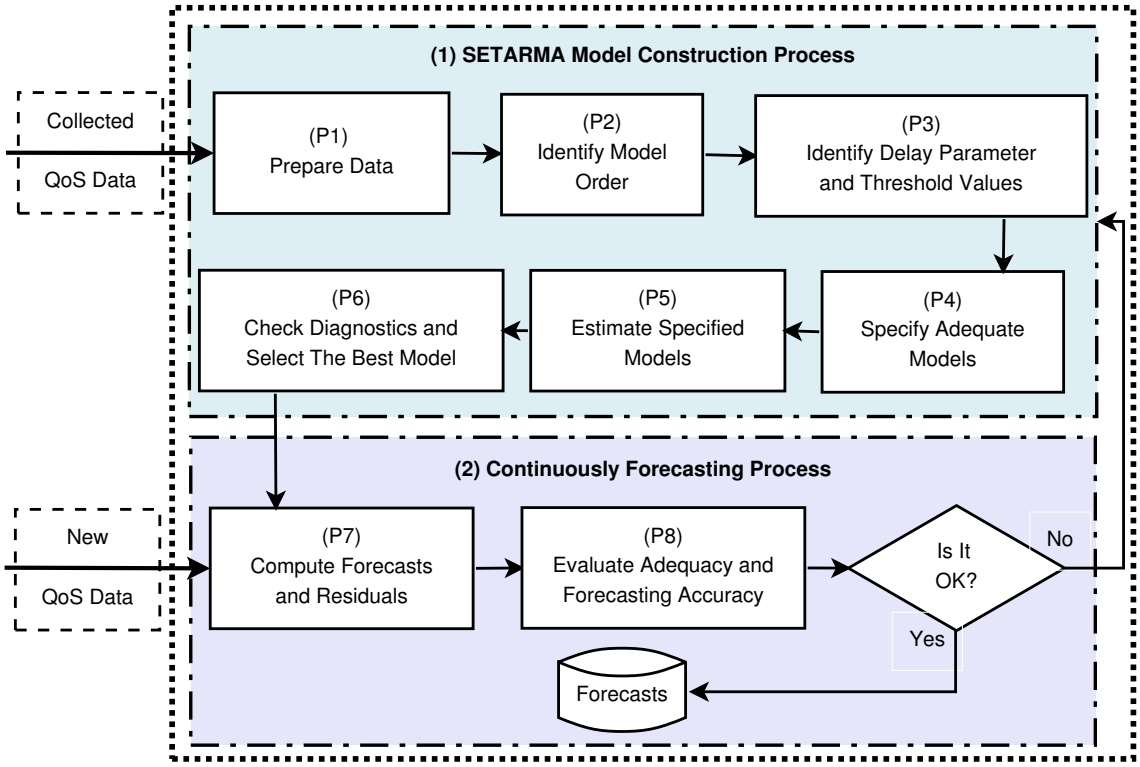


Figure 5.1: The proposed forecasting approach I based on SETARMA models

5.2.1 SETARMA Model Construction Process

The main task of this component is to construct a SETARMA model for the given QoS data. This is achieved through six phases, which are discussed in detail as follows:

5.2.1.1 (P1) Data Preparation

Before constructing a SETARMA model, the given QoS time series data should satisfy the underlying assumptions of SETARMA models which are described above. Consequently in this phase, the main task of the proposed forecasting approach is to check for these assumptions; and if they are not satisfied, it tries to find the suitable

[1] `http://www.datasprings.com/`

transformation to approximately fulfill the assumptions.

First, the forecasting approach checks for the serial dependency using the runs test [77]. Then, it checks for the normality and stationarity using the Kolmogorov-Smirnov (K-S) test [77] and the KPSS test [115], respectively. In case that the QoS data is non-normally distributed, the approach uses the Box-Cox transformations [32] to achieve the normality. On the other hand, it uses the differencing method to produce a stationary QoS data.

Example ▷ The proposed forecasting approach I prepares the $WS_1(RT)$ data as follows:

Serial dependency: The forecasting approach applies the runs test to $WS_1(RT)$ data and concludes that it is significantly serially dependent with a p-value < 0.05.

Normality: The forecasting approach applies the K-S test to $WS_1(RT)$ and concludes that it is not normally distributed; however, the transformation parameter of value "0.75" provides approximately normally distributed data which is referred as $WS_1(TRT)$.

Stationarity: The forecasting approach uses the KPSS test to test whether the time series $WS_1(TRT)$ is stationary, and finds that it is stationary where the p-value equals to 0.238 (> 0.05). Therefore, the output of this phase is the dataset $WS_1(TRT)$ that satisfies the assumptions and can be used in the next phases. ◁

5.2.1.2 (P2) Initial Model Order Identification

After preparing the QoS time series data, the forecasting approach identifies initial values for the parameters p and q which determine an initial order for the SETARMA model. The approach achieves this task based on evaluating the autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the given QoS data [33].

Simply, the ACF is cross-correlations of the QoS time series data with itself at

different time lags, and the autocorrelation at lag k is computed as follows [33]:

$$r_k = \frac{\sum_{t=1}^{n-k}(y_t - \bar{y})(y_{t+k} - \bar{y})}{\sum_{t=1}^{n}(y_t - \bar{y})^2}, \qquad k = 0, 1, 2, \ldots \tag{5.8}$$

Regarding the PACF, generally the partial correlation between two variables is the pure correlation of these two variables after eliminating the possible impact of all other random variables that are correlated with them. To apply that to QoS time series data, the PACF is computed as follows [33]:

$$\phi_k = \frac{\begin{vmatrix} 1 & r_1 & \ldots & r_1 \\ r_1 & 1 & \ldots & r_2 \\ \vdots & \vdots & \vdots & \vdots \\ r_{k-1} & r_{k-2} & \ldots & r_k \end{vmatrix}}{\begin{vmatrix} 1 & r_1 & \ldots & r_{k-1} \\ r_1 & 1 & \ldots & r_{k-2} \\ \vdots & \vdots & \vdots & \vdots \\ r_{k-1} & r_{k-2} & \ldots & 1 \end{vmatrix}}, \qquad k = 0, 1, 2, \ldots \tag{5.9}$$

where, r_k is the autocorrelation coefficient at time lag k.

The ACF and PACF are used to identify the initial order of the SETARMA model as follows. If the ACF curve decays and the PACF curve cuts off (after p lags), a SETAR model (of order p) might be adequate to fit the processed data. In contrast, if the ACF curve cuts off (after q lags) and the PACF curve decays, a SETMA model (of order q) might be adequate. In addition, if both the ACF and PACF curves cut off after q and p lags respectively, a SETARMA model (of order p and q) might be adequate. Identifying the values of p and q is important for the next phase P3 to specify the delay parameter and thresholds values which are required as essential parameters for the SETARMA model.

Example ▷ The forecasting approach computes the ACF and PACF of the prepared data WS_1(TRT), which are plotted in Figure 5.2. From this Figure it can

be seen that the ACF decays and the PACF cuts off after 2 lags. Therefore, the approach identifies the initial order of the SETARMA model as $p = 2$ and $q = 0$. ◁

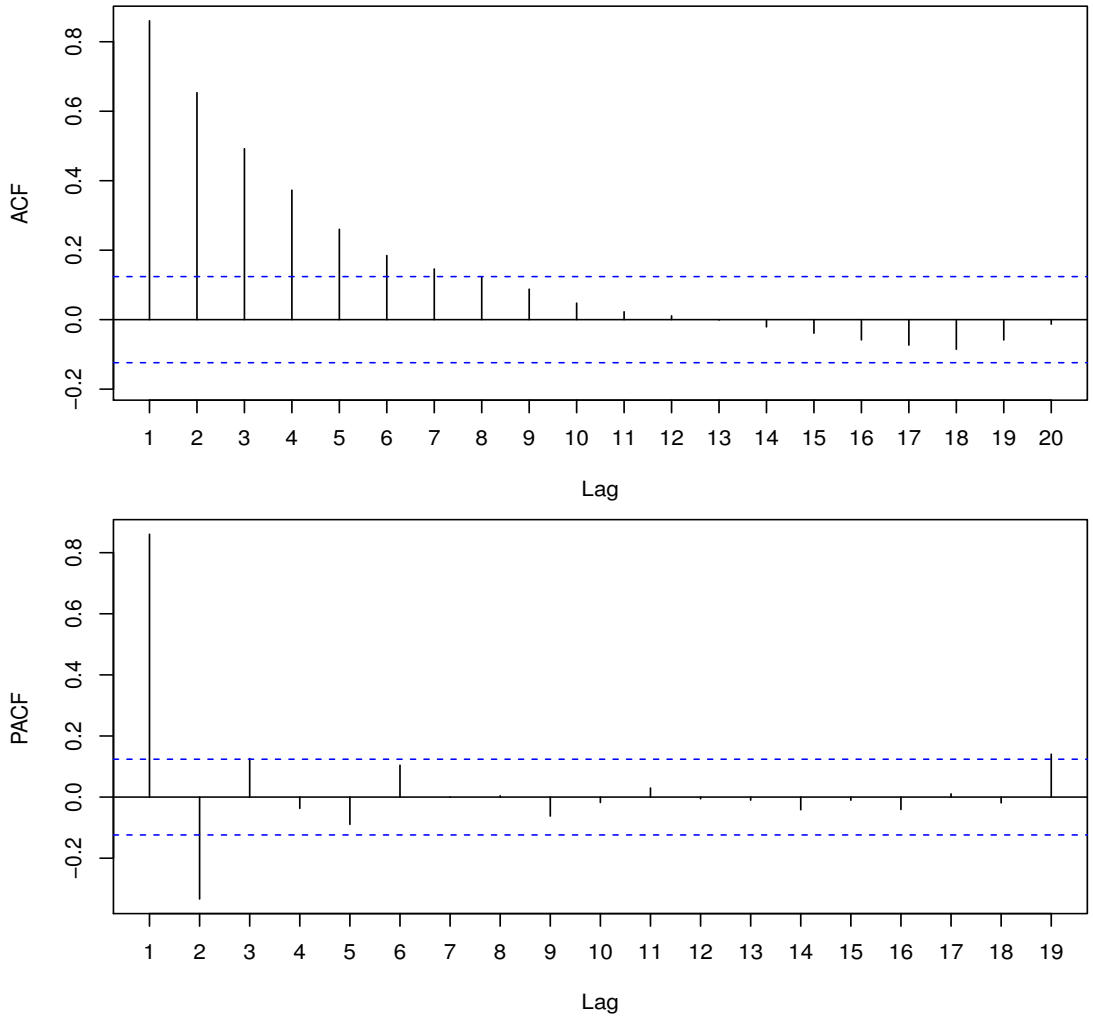


Figure 5.2: ACF and PACF values of WS_1(TRT)

5.2.1.3 (P3) Delay Parameter and Thresholds Identification

In this phase the forecasting approach needs to identify the values of delay parameter and thresholds. To achieve this, the approach uses the Hansen test [90], which is

introduced in Chapter 4. This test requires the parameter p and the delay parameter d_p as inputs. Although the value of the parameter p is already identified in P2 and can be used by the test, the delay parameter d_p is unknown and the approach needs to identify. Therefore, the approach runs the Hansen test different times with all the possible values of the delay parameter, which are any value less than the parameter p, *i.e.* $0 < d_p \leq p$. After that, based on the outputs of the Hansen tests the proposed approach refines the delay parameter value as the value that corresponds the largest statistic value of the significant Hansen test. Similarly, the thresholds values are identified as the values that correspond the largest statistic value.

Example ▷ Since the forecasting approach found in P2 that $p = 2$, it runs the Hansen test two times with inputs ($p = 2$ and $d_p = 1$) and ($p = 2$ and $d_p = 2$), and the output is depicted in Table 5.1. The forecasting approach concludes that the delay parameter $d_p = 2$ and the threshold value is 196.32. ◁

Delay Value	Threshold Estimate	Statistic Value	P-value
1	198.25	17.76	0.032
2	196.32	12.36	0.018

Table 5.1: Hansen test results for WS_1(TRT)

5.2.1.4 (P4) Adequate Models Specification

After identifying the initial model order, delay parameter and threshold values, the proposed forecasting approach specifies a combination of adequate SETARMA models for the given QoS dataset. This combination is based on the dependency structure of the given QoS dataset, in terms of the ACF and PACF, and under-fitting and over-fitting methods. Let p and q be the initial model order and d_p be the delay parameter, then the combination of adequate SETARMA models that can be specified are SETARMA$(l, p \pm i, q \pm j)$ for $i = 1, 2$ and $j = 1, 2$ with the

conditions that $(p-i) \geq d_p$, $(q-j) \geq 0$, $(p+i) \leq 5$ and $(q+j) \leq 5$, assuming that "5" is the highest order of the SETARMA models that can be fitted. This assumption of the highest order is based on our experience, however, this value can be easily changed and adapted to other values.

Example ▷ As the identified initial order of the SETARMA model is $p = 2$ and $q = 0$ and the delay parameter is $d_p = 2$, then based on the under-fitting and over-fitting methods the forecasting approach identifies nine SETARMA models for WS_1(TRT) with the orders that are the combination of $p = 2, 3, 4$ and $q = 0, 1, 2$. ◁

5.2.1.5 (P5) Models Estimation

In the models estimation phase, the forecasting approach estimates the parameters of the specified adequate models in phase P4 to provide the best fit for the given QoS time series data. The maximum likelihood estimation (MLE) [33] and conditional least squares (CLS) [227] are the most commonly used methods to estimate the SETARMA models' parameters. However, Chan [47] showed that the CLS method gives consistent estimators, which means that the estimates approach the true values of the parameters with increasing sample size. Therefore, the CLS method is adopted by the proposed forecasting approach I.

To briefly explain how the CLS method works, in the beginning, without loss the generality of the SETARMA model (5.6), the SETARMA$(2, p, q)$ model with the delay parameter d_p and the threshold value r (and assuming the homoscedasticity, *i.e.* $\varepsilon_t^{(j)} = \varepsilon_t$ for $j = 1, \ldots, l$) can be rewritten as follows:

$$y_t = \Omega_1^T A_t I[y_{t-d_p} \leq r] + \Omega_2^T A_t I[y_{t-d_p} > r] + \varepsilon_t \tag{5.10}$$

where Ω_j is the vector of SETARMA parameters of the jth regime, *i.e.* $\Omega_j = (\phi_1^{(j)}, \ldots, \phi_p^{(j)}, \theta_1^{(j)}, \ldots, \theta_q^{(j)})^T$ for $j = 1, 2$; A_t is the lagged values of the given QoS data represented in a data matrix, *i.e.* $A_t = (1, y_{t-1}, y_{t-2}, \ldots, y_{t-p})^T$; and $I[\cdot] \in$

$\{0, 1\}$ is the indicator function. Then, the estimate of $\Omega = (\Omega_1^T, \Omega_2^T)^T$ can be easily obtained by minimizing the conditional sum of squared errors, i.e. $(y_t - \Omega^T A_r)^T (y_t - \Omega^T A_r)$, and written as follows:

$$\hat{\Omega}_{(r)} = (A_{(r)}^T A_{(r)})^{-1} A_{(r)}^T y_t \tag{5.11}$$

where $A_{(r)} = (A_t^T I[y_{t-d_p} \leq r], A_t^T I[y_{t-d_p} > r])$ and from the used notation $\hat{\Omega}_{(r)}$ the estimate of Ω is conditional upon the threshold value r. It is worth mentioning that in the case of homoscedasticity, minimizing the residual sum of squares is equivalent to maximizing the log-likelihood function. In other words, CLS estimates are equivalent to those are given by maximum likelihood method.

Example ▷ After identifying the adequate SETARMA models in P4, the forecasting approach uses the CLS method for each model to estimate the parameters. The estimates of four of these identified SETARMA models are depicted in Table 5.2. ◁

5.2.1.6 (P6) Models Checking and the Best Model Selection

The forecasting approach checks the diagnostics of the SETARMA models to identify whether they are satisfied, and these diagnostics include the estimates significance test, satisfaction of the stationarity and invertibility conditions and residuals randomness. If one or more diagnostics are not satisfied, the current model is inadequate and it is necessary to be removed from the set of models specified in P4. These diagnostics are discussed in detail as follows.

Model	Regime	Parameter	Estimate	t-value	P-value
I	Low	SETAR(1)	0.757	6.215	0.000
		SETAR(2)	-0.177	-2.456	0.032
	High	SETAR(1)	0.270	2.751	0.026
		SETAR(2)	0.099	2.615	0.036
II	Low	SETAR(1)	-0.715	-5.115	0.000
		SETAR(2)	-0.084	-2.661	0.028
		SETMA(1)	0.433	2.456	0.038
	High	SETAR(1)	0.669	2.436	0.047
		SETAR(2)	0.074	2.499	0.041
		SETMA(1)	-0.325	-2.233	0.044
III	Low	SETAR(1)	-0.552	-7.652	0.000
		SETAR(2)	-0.064	-3.121	0.028
		SETAR(3)	0.051	2.856	0.033
	High	SETAR(1)	0.268	2.897	0.025
		SETAR(2)	0.187	2.775	0.041
		SETAR(3)	-0.075	-2.985	0.022
IV	Low	SETAR(1)	-0.848	-6.235	0.000
		SETAR(2)	-0.076	-3.231	0.029
		SETAR(3)	0.065	2.654	0.032
		SETMA(1)	0.523	2.561	0.028
	High	SETAR(1)	0.467	2.994	0.029
		SETAR(2)	0.074	2.325	0.042
		SETAR(3)	-0.043	-2.661	0.026
		SETMA(1)	-0.456	-3.123	0.035

Table 5.2: Estimation of four identified SETARMA models

Estimates Significance Test

Each estimate is tested to check whether it is statistically significant using the t-test, which its statistic is computed as follows:

$$t - statistic = \frac{estimate\ value}{standard\ error\ of\ estimate} \tag{5.12}$$

If all the estimates are significant, they are retained in the model; and otherwise, the model requires a recalculation using only the significant estimates.

Stationarity and Invertibility Conditions Satisfaction

Stationarity and invertibility conditions for the general SETARMA model are still under research, however, the forecasting approach I exploits the idea that at each regime there is an ARMA model and thus applies the stationarity and invertibility conditions of the general ARMA model. This means that the stationarity and invertibility conditions for the SETARMA model can be initially checked as follows: (1) Stationarity condition: The sum of the coefficients of the AR model at each regime should be less than one, which means that $\sum_{i=1}^{p} \phi_i^{(j)} < 1$ for $j = 1, 2, \ldots, l$; and (2) Invertibility condition: The sum of the coefficients of the MA model at each regime should be less than one, which means that $\sum_{i=1}^{q} \theta_i^{(j)} < 1$ for $j = 1, 2, \ldots, l$.

Residuals Randomness

Residuals of the well constructed SETARMA model should be uncorrelated and do not have any non-random pattern, which confirms that the model fits successfully the given QoS data. Therefore, the forecasting approach analyzes the residuals and performs a hypothesis test, *i.e.* the Box-Pierce test [34], to make a statistically significant decision regarding the residuals randomness.

Once the specified SETARMA models have been estimated and checked, the forecasting approach selects the best SETARMA model based on the Akaike's infor-

mation criterion (AIC) [1] where the best model is the one that has the minimum AIC value. Hence AIC is an increasing function of the number of estimated parameters. This makes AIC biased to the overfitted models. Therefore, AIC is corrected by penalizing the number of parameters as follows [103]:

$$AICc = AIC + \frac{2k(k+1)}{n-k-1} \tag{5.13}$$

where k and n are the number of parameters in the estimated model and the number of observations used to estimate the model, respectively. Following the recommendations in [36], AICc is used by the proposed forecasting approach.

At the end, the selected best SETARMA model can be written as follows:

$$y_t = \hat{\mu}^{(j)} + \sum_{i=1}^{p_j} \hat{\phi}_i^{(j)}\ y_{t-i} + \sum_{s=0}^{q_j} \hat{\theta}_s^{(j)}\ \varepsilon_{t-s} \qquad if \quad r_{j-1} \leq y_{t-d_p} < r_j \tag{5.14}$$

where $\hat{\phi}_i^{(j)}$'s and $\hat{\theta}_s^{(j)}$'s for $j = 1, 2, \ldots, l$ are the conditional least squares estimates.

Example ▷ The forecasting approach computes the t-test values and its p-values for all the estimates of the nine SETARMA models, and it finds that the estimates of four models are significant, and the other five models have insignificant estimates. Therefore, the approach ignores these five models and focuses only on the four models, which their t-values and p-values are depicted in Table 5.2. It is evident from Table 5.2 that these models satisfy invertibility and stationarity conditions. To analyze the residuals of the four models, the approach uses the Box-Pierce test [34] and concludes that only the residuals of the last two models are uncorrelated. Now based on the AICc value the forecasting approach selects the best model of those two models, where the AICc values are: 1810.53 and 1790.34 respectively. Accordingly, the fourth model, SETARMA$(2, 3, 1)$, is the best model to forecast the future values of $\mathrm{WS}_1(\mathrm{RT})$. ◁

5.2.2 Continuously Forecasting Process

The main task of this component is to use the selected best SETARMA model and the new obtained QoS data to continuously forecast the future QoS values and evaluate the adequacy and forecasting accuracy of the used SETARMA model, which is achieved through two phases as discussed in detail as follows.

5.2.2.1 (P7) Computing Forecasts and Predictive Residuals

The proposed forecasting approach uses the selected best SETARMA model to forecast the one-step-ahead future QoS values by moving from time "t" to "t + 1" as follows:

$$\hat{y}_{t+1} = \hat{\mu}^{(j)} + \sum_{i=1}^{p_j} \hat{\phi}_i^{(j)}\ y_{t+1-i} + \sum_{s=0}^{q_j} \hat{\theta}_s^{(j)}\ \hat{\varepsilon}_{t+1-s}, \tag{5.15}$$

and to compute the predictive residuals as:

$$\hat{\varepsilon}_t = (y_t - \hat{y}_t). \tag{5.16}$$

Based on assuming that the new QoS data is continuously obtained, the approach continuously computes the QoS forecasts and their predictive residuals.

Example ▷ The forecasting approach uses the constructed SETARMA(2,3,1) model with its parameters estimated in P5 to forecast the future values of $WS_1(RT)$, and the one-step-ahead forecasts of the last 100 real response time observations and their predictive residuals are computed and depicted in Figure 5.3. ◁

5.2.2.2 (P8) Evaluating Adequacy and Forecasting Accuracy

There is no guarantee that the stochastic behavior of the given QoS data will remain constant over time. Therefore, the forecasting approach continuously evaluates the adequacy and accuracy of the used SETARMA model. The approach evaluates the adequacy by monitoring the predictive residuals. This is because the predictive

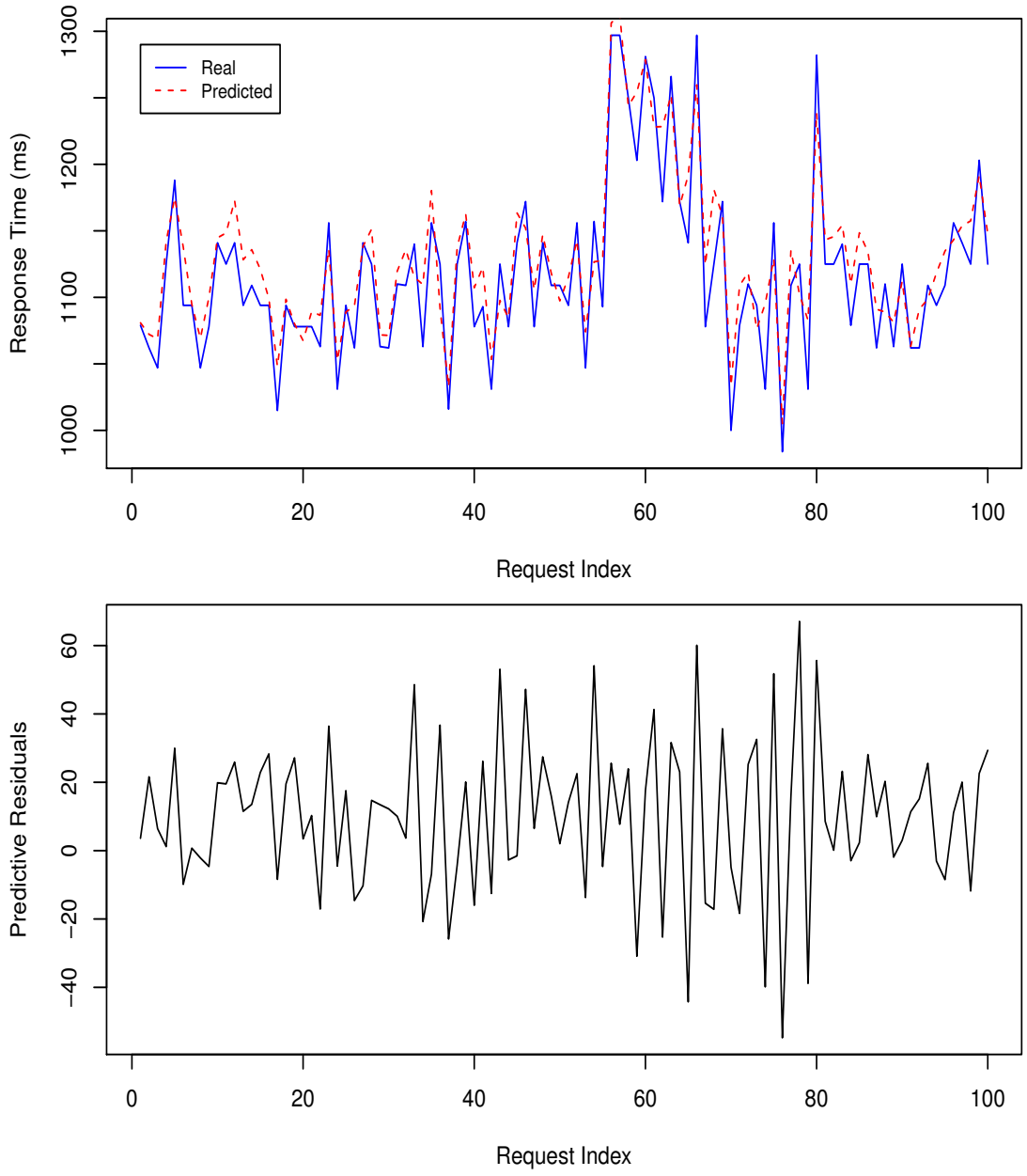


Figure 5.3: Real vs. predicted values of $WS_1(RT)$ and their predictive residuals

residuals of adequate SETARMA model fluctuate around zero; and the changes in the underlying QoS data will be immediately reflected in these predictive residuals which will no longer fluctuate around zero and a positive or negative drift will be introduced. To this end, the forecasting approach uses the CUSUM control chart [174] as an efficient technique to monitor the predictive residuals and detect their changes.

The CUSUM control chart monitors the predictive residuals by accumulating the deviations that are above zero (the target value) with the one-sided upper CUSUM statistic and deviations that are below zero with the one-sided lower CUSUM statistic. The one-sided upper and lower CUSUM statistics are computed respectively as follows:

$$C_t^+ = max[0, \hat{\varepsilon}_t - (\mu_0 + K) + C_{t-1}^+]$$

$$C_t^- = min[0, \hat{\varepsilon}_t - (\mu_0 + K) + C_{t-1}^-] \tag{5.17}$$

where the starting values are $C_0^+ = C_0^- = 0$, and $\mu_0 = 0$ is the target value. K is called the reference value for the CUSUM control chart and often selected to be $0.5\sigma_e$, where σ_e is the standard deviation of the predictive residuals [157]. Let H be the decision interval, and it is usually chosen to be $\pm 5\sigma_e$ [157]. Then, if the predictive residuals start to systematically have positive or negative drift, one of the CUSUM statistics will increase in magnitude till exceeds the decision interval H and an out-of-control signal will be generated. This signal indicates that the used SETARMA model is not adequate any more for the underlying QoS data and new SETARMA model has to be constructed. (Regarding the choice of K and H, Montgomery [157] introduces detailed discussion how these values can be chosen.)

In addition to monitoring the predictive residuals, the forecasting approach evaluates the forecasting accuracy by computing the mean absolute percentage error (MAPE) metric (in Equation 3.7), which is discussed in Chapter 3. Therefore, the MAPE value is used as a measure for the forecasting accuracy, where the smaller value indicates the higher forecasting accuracy and vice versa.

In the case that the CUSUM control chart signals that the used SETARMA

model is not adequate any more for the underlying QoS data or the forecasting accuracy is very low based on the MAPE metric, the forecasting approach will return back to the first component to re-identify and re-construct other adequate SETARMA model based on the new collected QoS data and the information obtained from the predictive residuals analysis.

Example ▷ The forecasting approach computes the CUSUM statistics for the predictive residuals, as depicted in Figure 5.4. It is clear from this Figure that the upper and lower CUSUM statistics do not exceed the decision interval, which indicates that the used SETARMA model is still adequate for the underlying response time data. In addition, the MAPE metric is computed and its value is 5.8%, which is relatively small and indicates to be accepted forecasting accuracy. ◁

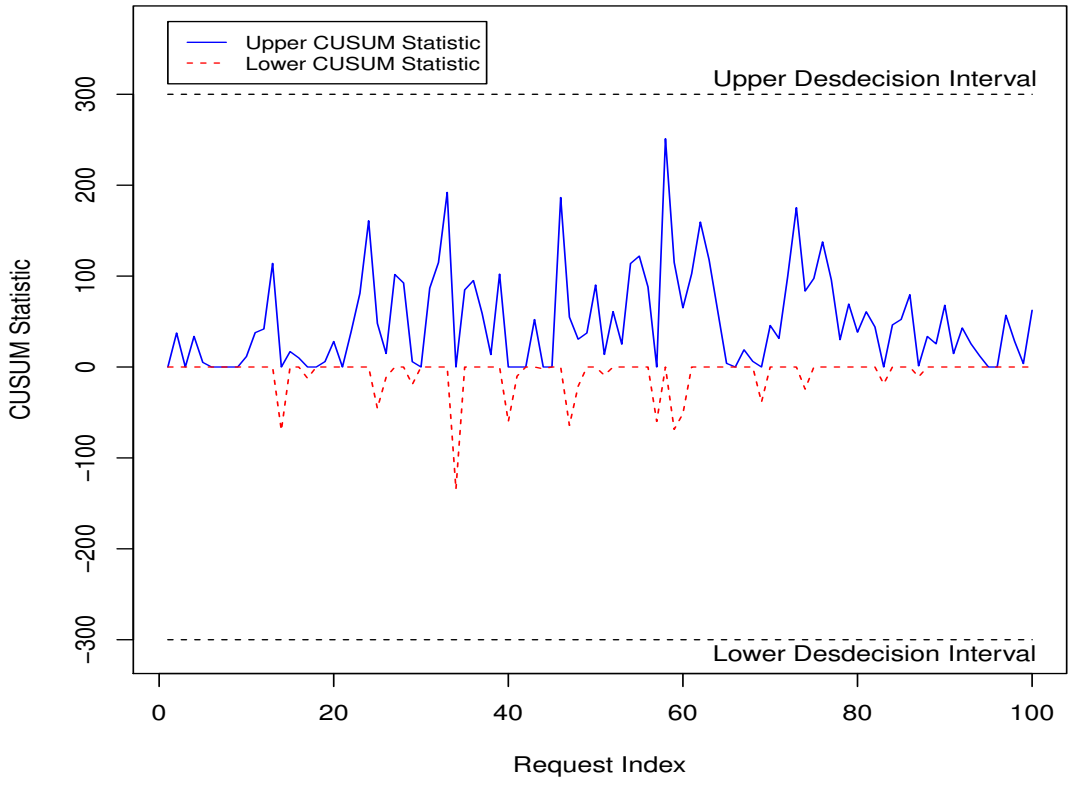


Figure 5.4: CUSUM statistics for the predictive residuals of $WS_1(RT)$

5.3 Summary

In this chapter, we first summarized the statistical background of the time series models and discussed their main assumptions. We then introduced the proposed forecasting approach I for nonlinearly dependent QoS attributes with a running example of response time of a real-world Web service. This forecasting approach is based on SETARMA time series models, and it will be able to effectively fit the nonlinear dynamic behavior of QoS attributes and accurately forecast their future values. However, the accuracy and performance of this forecasting approach need to be evaluated and compared to those of the baseline ARIMA models which is planned to be conducted in the evaluation chapter.

Chapter 6

Forecasting Approaches for Linearly Dependent QoS Attributes with Volatility Clustering

The objective of this chapter is to address the problem of forecasting linearly dependent QoS attributes with volatility clustering. Based on our review of the time series modeling literature, we have found that the generalized autoregressive conditional heteroscedastic (GARCH) models [28] is a promising method to fit the QoS volatility clustering and improve the ultimate QoS forecasting accuracy. Accordingly using the GARCH models, we propose two approaches to model the linearly dependent QoS attributes with volatility clustering:

- The first approach fits the given QoS data by ARIMA models, then computes the squared residuals, which include the volatility clustering, and fits by GARCH models.
- The second approach decomposes the given QoS data using wavelet analysis into two simplified sub-series: the general trend, which is purified from the

volatility clustering, and the noises component[1], which includes the volatility clustering. After that, it fits separately the general trend by ARIMA models and the noises component by ARIMA and GARCH models. Similar approach is proposed to forecast electricity price [223]

Consequently, in order to address the QoS volatility clustering and improving the QoS forecasting accuracy we propose two different forecasting approaches. The first forecasting approach, which is called forecasting approach II, is proposed based on ARIMA and GARCH models. The main idea of this forecasting approach is that it first constructs the best suitable ARIMA model for the given QoS data. It then computes the squared residuals, which include the volatility clustering, and constructs the best suitable GARCH model for the squared residuals. After that, using the new obtained QoS data, the forecasting approach continuously updates the constructed ARIMA-GARCH model, computes the QoS forecasts and evaluates the adequacy and forecasting accuracy of the constructed ARIMA-GARCH model.

On the other hand, the second forecasting approach, which is called forecasting approach III, is proposed based on the wavelet analysis, ARIMA and GARCH models. This forecasting approach first decomposes the complicated behavior of the given QoS data using wavelet analysis into two simplified sub-series which are the general trend and the noises component. Second, the forecasting approach constructs an ARIMA model for the general trend sub-series and an ARIMA-GARCH model for the noises component sub-series. Third, using the new obtained QoS data, the forecasting approach continuously updates the constructed ARIMA and ARIMA-GARCH models, computes the forecasts of the general trend and noises component respectively, combines these forecasts to provide the original QoS forecasts and evaluates the adequacy and forecasting accuracy of the constructed models. Although these two forecasting approaches II and III address the QoS volatility clustering, they are not expected to be identical in terms of forecasting accuracy and performance.

[1]As a note on terminology, "noises component" is used as a specific term in this thesis which refers to a high frequency component of the given QoS time series data, and it does not refer to the generic term of white noises.

In the rest of this chapter, we summarize the background of the GARCH models and Wavelet Analysis. We then introduce the proposed forecasting approaches II and III with a running example of response time of a real-world Web service.

6.1 Background of GARCH Models and Wavelet Analysis

This section introduces the background of GARCH time series models and wavelet analysis.

6.1.1 GARCH Models

The autoregressive conditional heteroscedastic (ARCH) models were introduced by Engle [68] to model the high volatility by describing the dynamic changes in time-varying variance as a deterministic function of past errors. These models have become widely accepted for financial time series with volatility clustering and turned out to be an important tool in the field of financial forecasting [102, 124].

Engle formally defined the ARCH model for a conditional variance σ_t^2 of the dependent variable y_t as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_m \varepsilon_{t-m}^2, \tag{6.1}$$

where, $\varepsilon_t = y_t - \sum_{i=1}^{p} \phi_i y_{t-i} - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$, and m and $\alpha_i \; for \; i = 0, ..., \; m$ are the ARCH model order and coefficients respectively.

A generalization of ARCH model (GARCH) where additional dependencies are permitted on lags of the conditional variance was introduced by Bollerslev [28]. Mainly, in GARCH model the conditional variance is more generalized than in ARCH model and can be written as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{r} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=0}^{m} \beta_j \sigma_{t-j}^2. \tag{6.2}$$

with constraints,

$$\alpha_0{>}0,\ \alpha_i \geq 0,\ \beta_j \geq 0,\ and\ \sum_{i=1}^{r}\alpha_i + \sum_{j=0}^{m}\beta_j < 1. \tag{6.3}$$

6.1.2 Wavelet Analysis

Wavelet analysis is a mathematical technique which breaks up a time series (signal) into wavelets based on a specific wavelet transform [140]. More specifically, the wavelet transform is a scaling function which converts a signal into a low and high frequency components, which represent the general trend and noises component in the original time series data respectively.

A time series y_t can be decomposed into a series of wavelets as follows. First, the scaling function $\varphi(t)$ which called the father wavelet is defined as $\int_{-\infty}^{+\infty}\varphi(t)dt = C$, where C is a constant, and the wavelet function $\psi(t)$ which called the mother wavelet is defined as $\int_{-\infty}^{+\infty}\psi(t)dt = 0$. These father and mother wavelets are orthogonal to each other, *i.e.* $\int_{-\infty}^{+\infty}\varphi(t)\psi(t)dt = 0$, and their successive wavelets are obtained as follows:

$$\begin{aligned} \varphi_k(t) &= \varphi(t-k), \quad k \in Z \\ \psi_{k,j}(t) &= 2^{2/j}\psi(2^j t - k), \quad (k,j) \in Z \end{aligned} \tag{6.4}$$

where k is a time factor and j is a scaling index. Then, the decomposition coefficients of the wavelet transform of the original time series y_t can be computed as follows:

$$\begin{aligned} w^{\Phi}(k) &= \int_{-\infty}^{+\infty} y_t\varphi_k(t)dt \\ w^{\Psi}(k,j) &= \int_{-\infty}^{+\infty} y_t\psi_{k,j}(t)dt \end{aligned} \tag{6.5}$$

Using the computed decomposition coefficients, the general trend (GT_t) and noises component (NC_t) of the original time series data can be computed respectively as

follows:

$$\begin{aligned} GT_t &= \sum_{k=-\infty}^{+\infty} w^{\Phi}(k)\varphi_k(t) \\ NC_t &= \sum_{k=-\infty}^{+\infty}\sum_{j=-\infty}^{+\infty} w^{\Psi}(k,j)\psi_{k,j}(t) \end{aligned} \tag{6.6}$$

6.2 Forecasting Approach II Based on ARIMA and GARCH Models

The proposed forecasting approach II integrates ARIMA and GARCH models to capture the QoS volatility clustering and accurately forecast their future values. In brief summary, the forecasting approach first constructs the ARIMA model for the given QoS data, and then computes the squared residuals, which include the volatility clustering, and constructs the GARCH model. After that, using the new obtained QoS data, the forecasting approach continuously updates the constructed ARIMA-GARCH model, computes the QoS forecasts, and evaluates the adequacy and forecasting accuracy of the constructed ARIMA-GARCH model. Consequently, this forecasting approach consists of three components: ARIMA model construction process, GARCH model construction process, and continuously forecasting process; as explained in Figure 6.1. In the following the proposed forecasting approach II is introduced in detail and explained by a running example of the response time dataset (which is referred as $WS_2(RT)$) of the web service "GlobalWeather"[1] which provides the current weather along with additional information for major cities around the world.

6.2.1 ARIMA Model Construction Process

This component uses the collected QoS data to construct the ARIMA model through four phases as follows:

[1] `http://www.webservicex.com/globalweather.asmx`

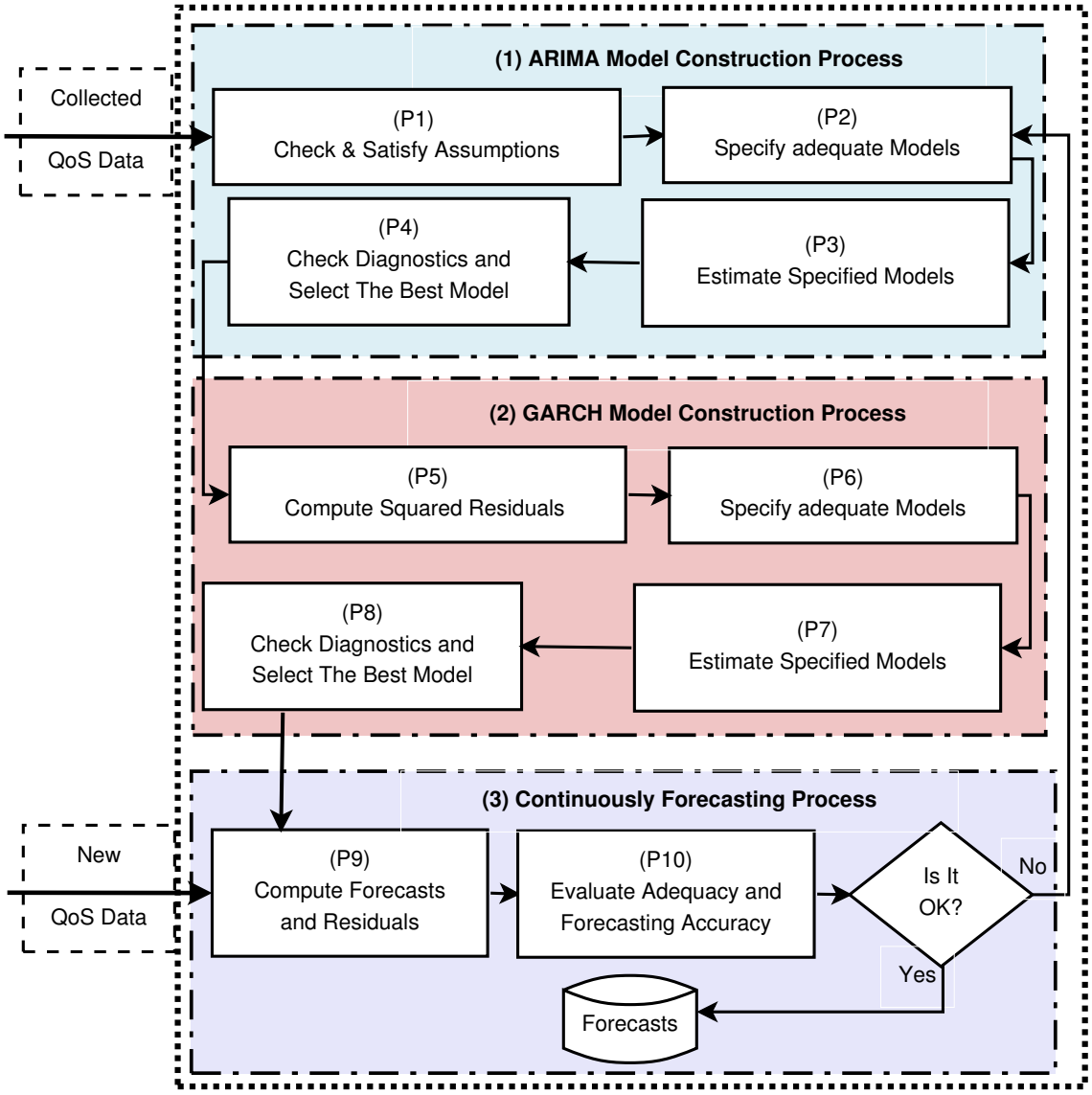


Figure 6.1: The proposed forecasting approach II based on ARIMA and GARCH models

6.2.1.1 (P1) Data Preparation

Similarly to the forecasting approach I in Chapter 5, the forecasting approach II uses some statistical tests to check for the underlying assumptions which include the serial dependency, normality and stationarity before constructs the ARIMA model. In addition, in the case that these assumptions are not satisfied, it tries to find a suitable transformation to make the given QoS data approximately fulfils them. In particular, the forecasting approach II checks for the serial dependency,

normality and stationarity using the runs test [77], the Kolmogorov-Smirnov (K-S) test [77], and the KPSS test [115], respectively. In addition, it uses the Box-Cox transformations [32] and the differencing method to achieve the normality and stationarize the given QoS data, respectively.

Example ▷ The proposed forecasting approach II prepares the WS_2(RT) data as follows:

Serial dependency: The forecasting approach applies the runs test to WS_2(RT) data and concludes that it is significantly serially dependent with a p-value < 0.05.

Normality: The forecasting approach applies the K-S test to WS_2(RT) and concludes that it is not normally distributed; however, the transformation parameter of value "-0.156" provides approximately normally distributed data which is referred as WS_2(TRT).

Stationarity: The approach uses the KPSS test to test whether the time series WS_2(TRT) is stationary, and finds that it is not stationary where the p-value equals to 0.039 (< 0.05). Using the first difference, the approach concludes that the differenced data (referred as WS_2(DTRT)) is stationary where the p-value equals to 0.493. ◁

6.2.1.2 (P2) Adequate Models Specification

After preparing the QoS data, the forecasting approach II identifies initial values for the parameters p and q of the ARIMA model which determine the initial model order. Similarly to the forecasting approach I in Chapter 5, the forecasting approach II uses ACF and PACF to achieve this task as follows. If the ACF curve decays and the PACF curve cuts off (after p lags), an AR model (of order p) might be adequate to fit the processed data. In contrast, if the ACF curve cuts off (after q lags) and the PACF curve decays, a MA model (of order q) might be adequate. In addition, if both the ACF and PACF curves cut off after q and p lags respectively, an ARMA model (of order p and q) might be adequate.

After identifying the initial model order, the proposed forecasting approach II specifies a combination of adequate ARIMA models for the given QoS dataset. Using the same notion of SETARMA models specification introduced in Chapter 5, the combination of ARIMA models is based on the dependency structure of the given QoS dataset, in terms of the ACF and PACF, and under-fitting and over-fitting methods. Let p and q be the initial model order and d be the differencing order determined in P1, then the combination of adequate ARIMA models that can be specified are ARIMA$(p \pm i, d, q \pm j)$ for $i = 1, 2$ and $j = 1, 2$ with the conditions that $(p - i) \geq 0$, $(q - j) \geq 0, (p - i) + (q - j) > 0$, $(p + i) \leq 5$ and $(q + j) \leq 5$, assuming that "5" is the highest order of the ARIMA models that can be fitted. This assumption of the highest order is based on our experience, however, this value can be easily changed and adapted to other values.

Example ▷ The forecasting approach computes the ACF and PACF of the prepared data, WS_2(DTRT), as plotted in Figure 6.2. From this Figure it can be seen that the ACF cuts off after 3 lags and the PACF decays. Therefore, the forecasting approach identifies the initial order of the ARIMA model as $p = 0$ and $q = 3$. It is worth noting that $d = 1$ is already determined in P1. Based on the identified initial ARIMA model order and the under-fitting and over-fitting methods the forecasting approach identifies fifteen ARIMA models for WS_2(DTRT) with the orders that are the combination of $p = 0, 1, 2$ and $q = 1, 2, 3, 4, 5$. ◁

6.2.1.3 (P3) Models Estimation

In models estimation phase, the forecasting approach II estimates the parameters of the identified combination of ARIMA models to provide the best fit to the given QoS data. Similarly to SETARMA models, maximum likelihood estimation (MLE) [33] and conditional least squares (CLS) [227] are the most commonly used methods to estimate the ARIMA models' parameters. However, the former one is generally the preferred technique to fit ARIMA models, as it is faster and gives more accurate

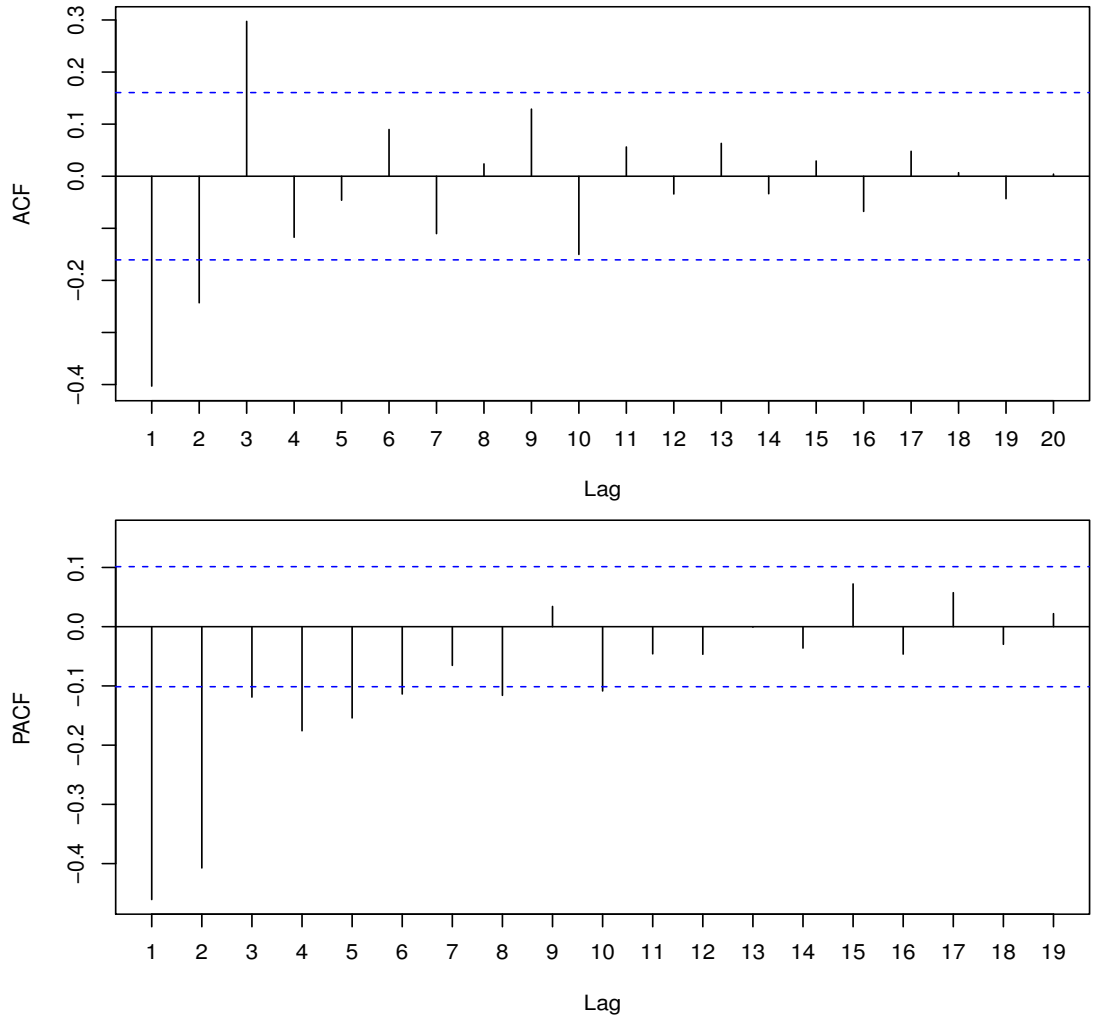


Figure 6.2: ACF and PACF values of WS_2(DTRT)

estimates [33]. Therefore, the MLE method is adopted by the proposed forecasting approach II.

To briefly explain how the MLE method works, suppose that y_t for $t = 1, 2, \ldots, n$ is a QoS time series modeled by the ARMA model (5.2), then the likelihood function, l, is given by

$$l \propto (\sigma^2)^{-\frac{n}{2}} \exp\left\{-\frac{1}{2\sigma^2}\sum_{t=1}^{n}\left(y_t - \sum_{i=1}^{p}\phi_i y_{t-i} - \sum_{i=1}^{q}\theta_i \varepsilon_{t-i}\right)^2\right\} \tag{6.7}$$

where the values of the parameters ϕ_i's and θ_i's that maximize the likelihood function (6.7) are called the maximum likelihood estimates.

Example ▷ After identifying the adequate ARIMA models in P2, the forecasting approach uses the MLE method for each model to estimate the parameters. The estimates of eight of these identified ARIMA models are depicted in Table 6.1. ◁

6.2.1.4 (P4) Models Checking and the Best Model Selection

This phase has the same functionality as P6 of the forecasting approach I in Chapter 5, where it evaluates the diagnostics of the ARIMA models to identify whether they are satisfied. If one or more diagnostics are not satisfied, the current ARIMA model is inadequate and it is necessary to be removed from the set of models identified in P2. These diagnostics include estimates significance, stationarity and invertibility conditions, and residuals randomness.

After evaluating the diagnostics, the best ARIMA model is selected based on the minimum AICc value. Then, the selected best ARIMA model can be written as follows:

$$y_t = \hat{\mu} + \sum_{i=1}^{p} \hat{\phi}_i y_{t-i} + \sum_{i=1}^{q} \hat{\theta}_i \hat{\varepsilon}_{t-i} \tag{6.8}$$

where $\hat{\phi}_i$'s and $\hat{\theta}_i$'s are the maximum likelihood estimates.

Example ▷ The forecasting approach computes the t-test values and its p-values for all the estimates of the fifteen ARIMA models, and it finds that the estimates of eight models are significant, and the other seven models have insignificant estimates. Therefore, the approach ignores these seven models and focuses only on the eight models, where their t-values and p-values are depicted in Table 6.1. It is evident from Table 6.1 that these models satisfy invertibility and stationarity conditions. The approach uses the Box-Pierce test [34] to analyze the residuals of the eight models and concludes that the residuals of the first five models are correlated and those of the last three models are uncorrelated. The forecasting approach selects

Model	Parameter	Estimate	t-value	P-value
I	AR(1)	-0.485	-13.499	0.000
II	AR(1)	0.144	2.526	0.024
	MA(1)	-0.971	-25.526	0.000
III	AR(1)	-0.677	-17.813	0.000
	AR(2)	-0.292	-10.315	0.001
IV	AR(1)	0.157	3.389	0.023
	AR(2)	0.128	2.766	0.034
	MA(1)	-0.985	-45.818	0.000
V	AR(1)	-0.804	-16.652	0.001
	AR(2)	-0.113	-2.237	0.042
	MA(1)	-0.107	-2.972	0.028
	MA(2)	-0.813	-24.598	0.000
VI	AR(1)	-0.738	-18.182	0.001
	AR(2)	-0.500	-10.742	0.002
	AR(3)	-0.159	-3.902	0.036
VII	AR(1)	0.163	3.998	0.035
	AR(2)	0.131	3.211	0.038
	AR(3)	0.130	3.108	0.039
	MA(1)	-0.956	-21.658	0.000
VIII	AR(1)	-0.225	8.018	0.003
	AR(2)	0.151	3.283	0.037
	AR(3)	0.142	3.558	0.032
	MA(1)	-0.707	-2.499	0.042
	MA(2)	-0.183	-2.212	0.044

Table 6.1: Estimation of eight identified ARIMA models

the best model of these three models based on the AICc value. The AICc values for those three models are: 1503.73, 1403.58 and 1402.49 respectively. Accordingly, the eighth model, ARIMA$(3, 1, 2)$, is the best model to forecast the future values of WS_2(TRT). ◁

6.2.2 GARCH Model Construction Process

This component uses the residuals of the selected best ARIMA model to construct the GARCH model, and this is achieved through four phases as follows:

6.2.2.1 (P5) Computing Squared Residuals

In this phase, the forecasting approach II uses the selected best ARIMA model to compute the squared residuals that need to be used to construct the GARCH model. Simply, this is achieved as follows:

$$\hat{\varepsilon}_t^2 = \left(y_t - \hat{\mu} - \sum_{i=1}^{p} \hat{\phi}_i y_{t-i} - \sum_{i=1}^{q} \hat{\theta}_i \hat{\varepsilon}_{t-i} \right)^2 \tag{6.9}$$

6.2.2.2 (P6 - P8) Adequate GARCH Model Construction

The forecasting approach II constructs the adequate GARCH model through phases (P6 - P8). These phases are functionally the same as phases (P2 - P4). The main difference is that in the diagnostics checking phase (P8) the approach does not check for the stationarity and invertibility where the GARCH model does not require these conditions, but needs to check for the GARCH model constraints in equation 6.3.

Example ▷ The forecasting approach computes the squared residuals and their ACF and PACF which are plotted in Figure 6.3. Since the ACF decays and PACF cuts off after 2 lags, the forecasting approach identifies the initial order of the GARCH model as $r = 2$ and $m = 0$.

Based on the identified initial GARCH model order and the under-fitting and

over-fitting methods, the forecasting approach identifies twelve GARCH models with the orders that are the combination of $r = 1, 2, 3, 4$ and $m = 0, 1, 2$. Then, the approach uses the MLE method for each model to estimate the parameters and computes the t-test values and its p-values for all the estimates; and it finds that the estimates of only four models are significant, which their t-values and p-values are depicted in Table 6.2. From this Table, it is evident that all the four models satisfy the GARCH's conditions in equation 6.3.

The forecasting approach uses the AICc value to select the best model, where the AICc values for those four models are: 1361.09, 1341.58, 1362.29 and 1358.79 respectively. Consequently, the second model, GARCH$(1, 1)$, is the best model that can be used with ARIMA$(3, 1, 2)$ to forecast the future values of WS_2(TRT). ◁

Model	Parameter	Estimate	t-value	P-value
I	ARCH(1)	0.153	2.112	0.035
II	ARCH(1)	0.128	2.352	0.019
	GARCH(1)	0.638	3.928	0.000
III	ARCH(1)	0.149	2.305	0.021
	ARCH(2)	0.098	2.121	0.034
IV	ARCH(1)	0.124	1.975	0.048
	ARCH(2)	0.003	1.972	0.049
	GARCH(1)	0.635	2.673	0.008

Table 6.2: Estimation of four identified GARCH models

6.2.3 Continuously Forecasting Process

This component has the same functionality as the second component of the forecasting approach I in Chapter 5, where it uses the constructed ARIMA-GARCH model and the new obtained QoS data to continuously forecast the future QoS values and computes the predictive residuals (through phase P9). Additionally through phase

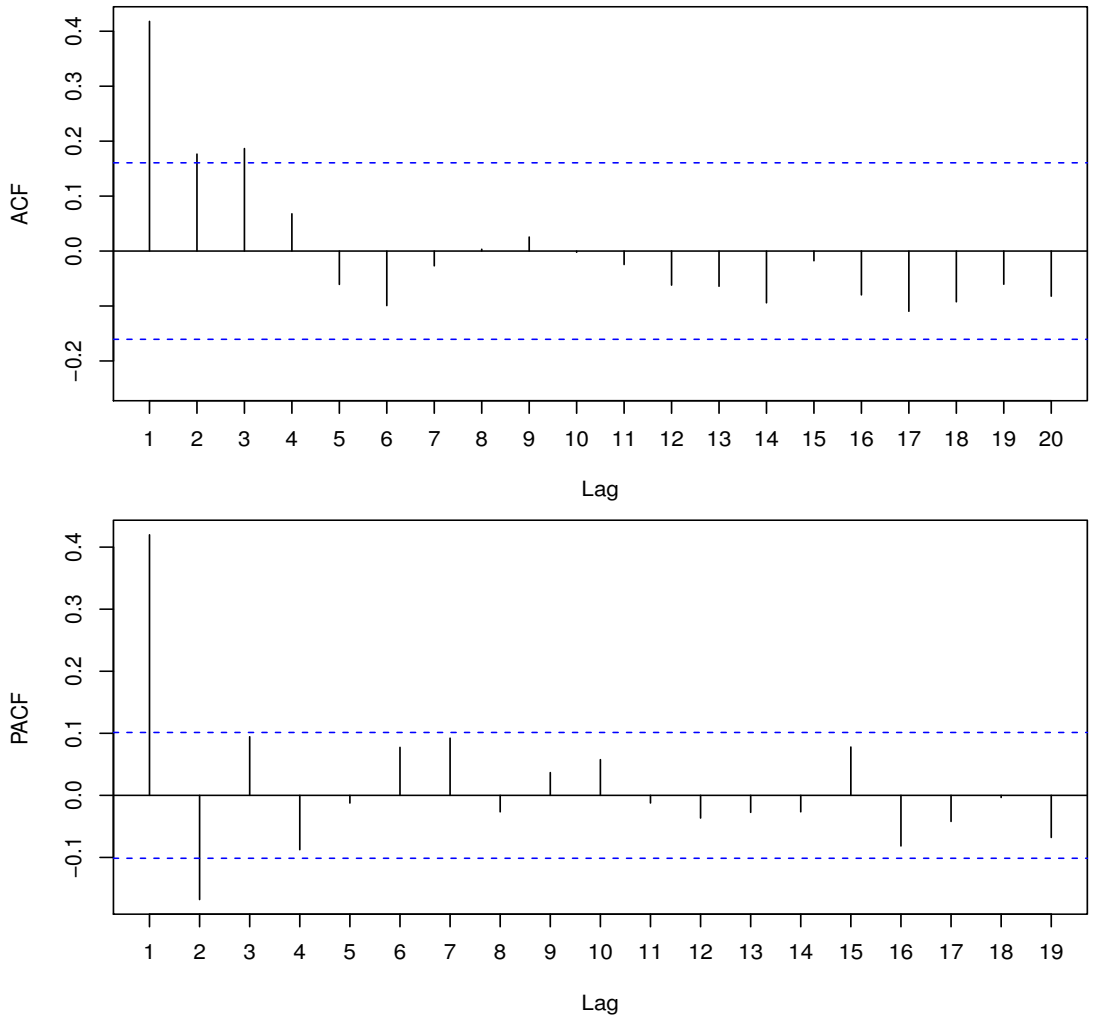


Figure 6.3: ACF and PACF values of the squared residuals of WS_2(TRT)

P10, it continuously evaluates the adequacy of the constructed ARIMA-GARCH model for the underlying QoS data using the CUSUM control chart and the forecasting accuracy using the MAPE measure.

In the case that the CUSUM control chart signals that the constructed ARIMA-GARCH model is not adequate any more for the underlying QoS data or the forecasting accuracy is very low based on the MAPE measure, the forecasting approach will return back to P2 to re-identify and construct other adequate ARIMA-GARCH model based on the new collected QoS data and the information obtained from the

predictive residuals analysis.

Example ▷ The forecasting approach uses the constructed ARIMA(3,1,2)-GARCH(1,1) model to forecast the future values of WS_2(RT), and the one-step-ahead forecasts of the last 100 observations and their predictive residuals are depicted in Figure 6.4. In addition, the approach computes the CUSUM statistics for the predictive residuals, as depicted in Figure 6.5. It is clear from this Figure that the upper and lower CUSUM statistics do not exceed the decision interval, which indicates that the used ARIMA(3,1,2)-GARCH(1,1) model is still adequate for the underlying response time data. Moreover, the MAPE measure is computed and its value is 5.9%, which is relatively small and indicates to be accepted forecasting accuracy. ◁

6.3 Forecasting Approach III Based on Wavelet Analysis, ARIMA and GARCH Models

The proposed forecasting approach III integrates wavelet analysis, ARIMA and GARCH models to decompose the complicated behavior of the given QoS data into two simplified sub-series to be able to capture the QoS volatility clustering and provide accurate QoS forecasting.

In brief summary, the forecasting approach III first uses the wavelet analysis to decompose the given QoS data into two sub-series; general trend sub-series, which is purified form the volatility clustering, and noises sub-series, which includes the volatility clustering. Second, the forecasting approach constructs an ARIMA model for the general trend sub-series and an an ARIMA-GARCH model for the noises sub-series. Third, using the new obtained QoS data, the forecasting approach continuously updates the constructed ARIMA and ARIMA-GARCH models, computes the forecasts of the general trend and noises sub-series respectively, combines these forecasts to provide the original QoS forecasts and evaluates the adequacy and forecasting accuracy of the constructed models.

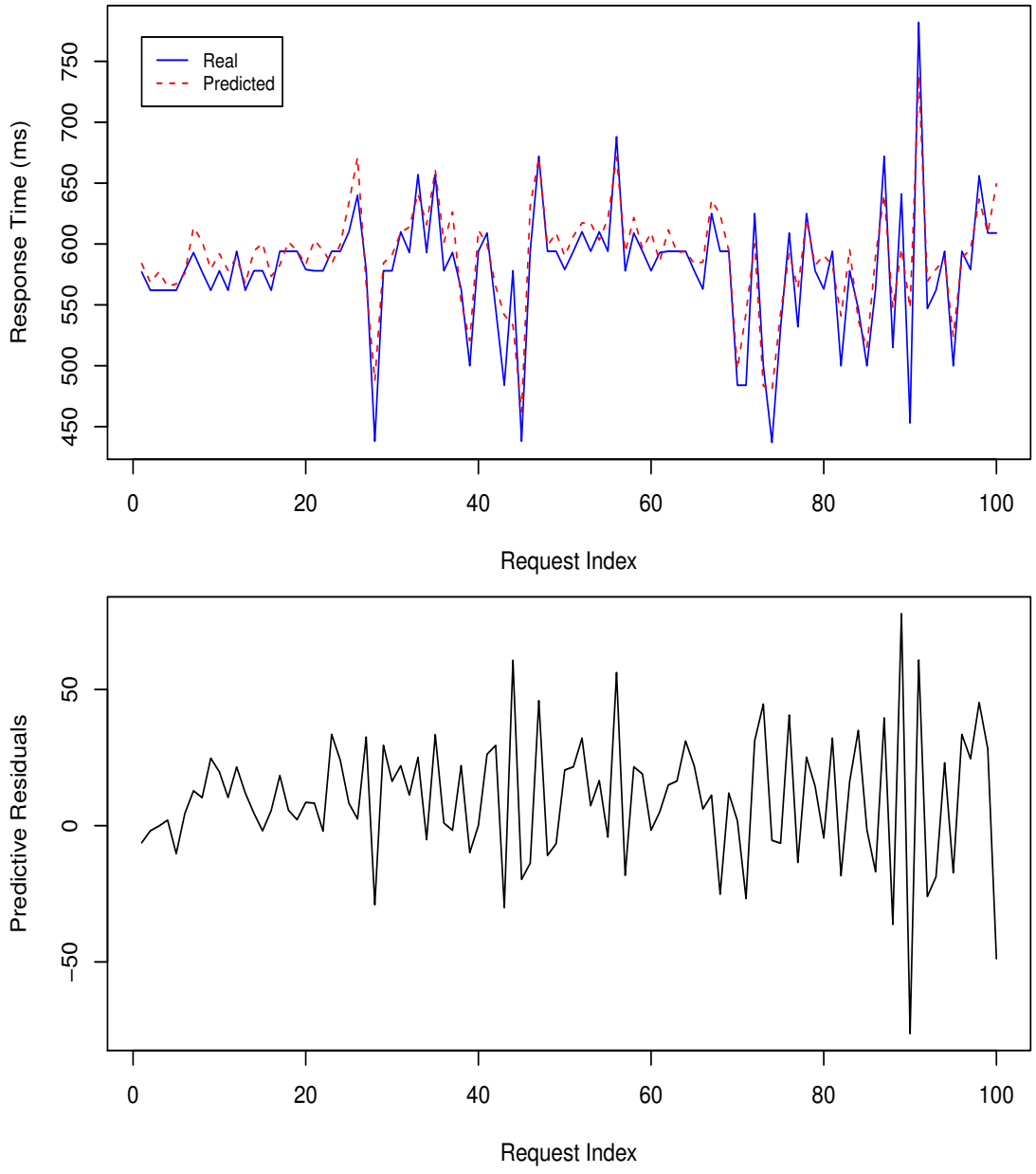


Figure 6.4: Real vs. predicted values of $WS_2(RT)$ and their predictive residuals for the forecasting approach II

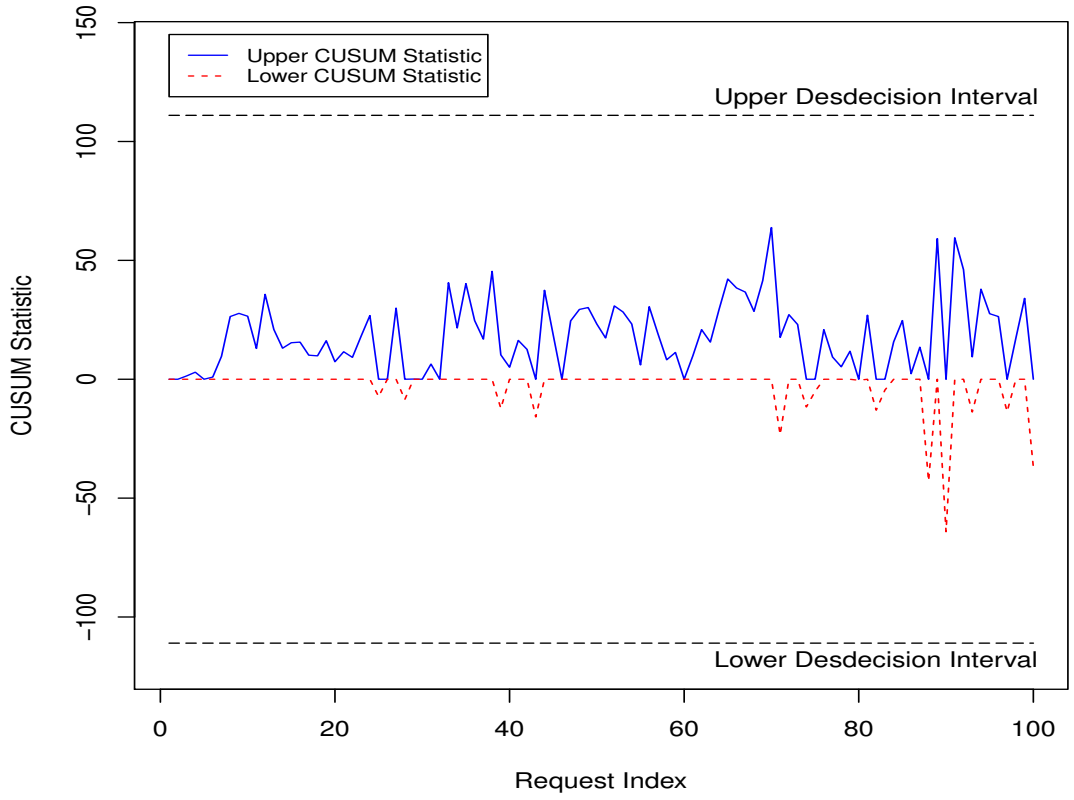


Figure 6.5: CUSUM statistics for the predictive residuals of $WS_2(RT)$ for the forecasting approach II

Consequently, this approach consists of three components: Wavelet-based QoS time series decomposition, ARIMA and ARIMA-GARCH models construction process for the general trend and noises sub-series respectively, and continuously forecasting process; as explained in Figure 6.6. In the following the functionalities of each component will be introduced with a running example of the same response time dataset used in Section 6.2.

6.3.1 Wavelet-Based QoS Time Series Decomposition

This component uses wavelet analysis to decompose the given QoS data into the general trend and noises component sub-series through two phases as follows.

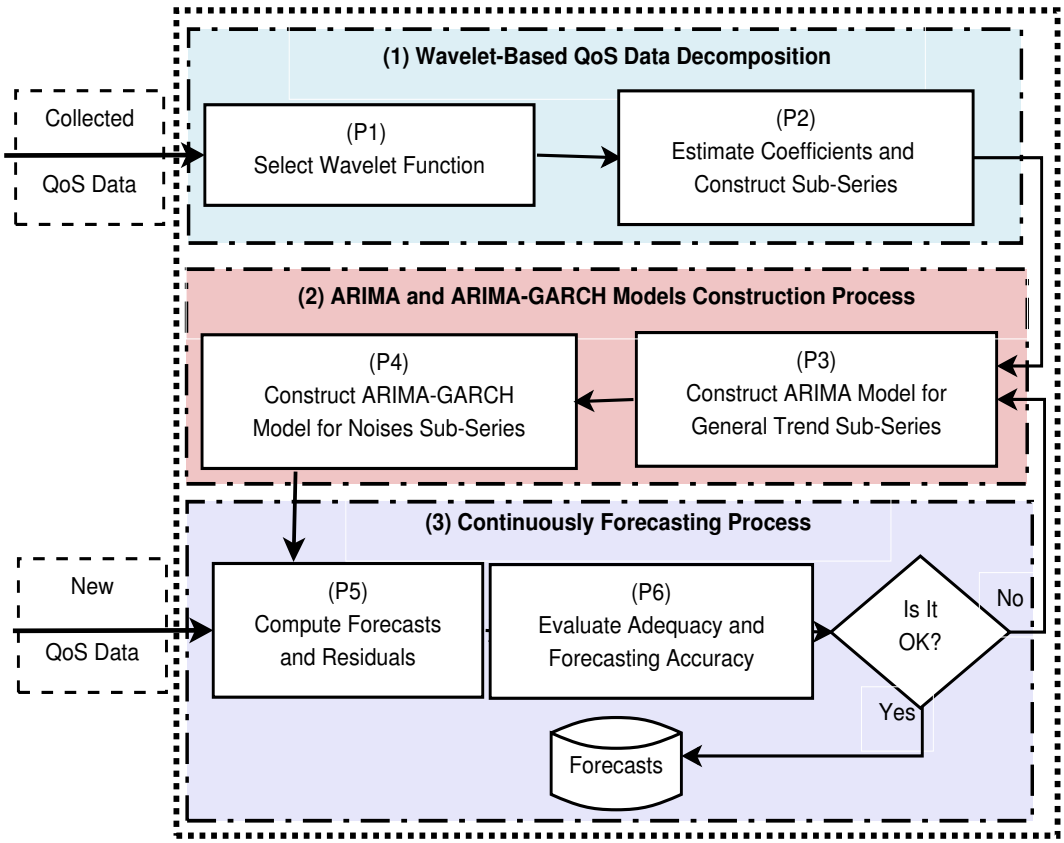


Figure 6.6: The proposed forecasting approach III based on Wavelet analysis, ARIMA and GARCH models

6.3.1.1 (P1) Selecting Wavelet Function

In this phase, the forecasting approach III selects a wavelet function that can be used to fit the QoS data under analysis. This wavelet function is expressed into two functions, father $\varphi(t)$ and mother $\psi(t)$ functions. Several wavelet functions are available such as Haar, Meyer and Daubechies wavelets [57, 140]. However, the forecasting approach III adopts the Daubechies wavelet function as it is efficient and the most commonly used in the practical applications [140].

Based on the Daubechies wavelet, the forecasting approach estimates the father wavelet by defining its Fourier transform as follows:

$$\hat{\varphi}(w) = \frac{1}{\sqrt{2\pi}} \prod_{j=-\infty}^{+\infty} m_0(w/2^j) \tag{6.10}$$

where w is a Fourier variable and $m_0(w)$ is a periodic function defined as $m_0(w) = e^{iw/2}cos(w/2)$. Then, the father wavelet estimate is obtained as $\hat{\varphi}(t) = F^{-1}(\hat{\varphi}(w))$, where F^{-1} is the inverse Fourier transform. After estimating the father wavelet, the mother wavelet is estimated as follows:

$$\hat{\psi}(t) = \sum_{k=-\infty}^{+\infty} b_k \hat{\varphi}(2t-k) \tag{6.11}$$

where b_k is given by:

$$b_k = \int_{-\infty}^{+\infty} \sqrt{2}\hat{\varphi}(2t-k)\hat{\varphi}(t)dt \tag{6.12}$$

6.3.1.2 (P2) Estimating Decomposition Coefficients and Constructing Sub-Series

After selecting the wavelet function and estimating the father and mother wavelets, the forecasting approach fits the given QoS data on the estimated functions and computes the decomposition coefficients as follows:

$$\begin{aligned} w^{\Phi}(k) &= \int_{-\infty}^{+\infty} y_t \hat{\varphi}_k(t)dt \\ w^{\Psi}(k,j) &= \int_{-\infty}^{+\infty} y_t \hat{\psi}_{k,j}(t)dt \end{aligned} \tag{6.13}$$

Then, the approach uses the computed decomposition coefficients and the estimated father and mother functions to construct the general trend (GT_t) and noises component (NC_t) as follows:

$$\begin{aligned} GT_t &= \sum_{k=-\infty}^{+\infty} w^{\Phi}(k)\hat{\varphi}_k(t) \\ NC_t &= \sum_{k=-\infty}^{+\infty}\sum_{j=-\infty}^{+\infty} w^{\Psi}(k,j)\hat{\psi}_{k,j}(t) \end{aligned} \tag{6.14}$$

Example ▷ The forecasting approach III uses the wavelet analysis to decompose the WS_2(RT) dataset into the general trend and noises component sub-series. The WS_2(RT) dataset and the constructed general trend and noises component sub-series are depicted in Figure 6.7. ◁

6.3.2 ARIMA and ARIMA-GARCH Models Construction Process

The main task of this component is to construct an ARIMA model for the general trend (GT_t) and an ARIMA-GARCH model for the noises component (NC_t) through two phases as follows.

6.3.2.1 (P3) Constructing ARIMA Model for the General Trend

In this phase, the forecasting approach III constructs an ARIMA model for the general trend GT_t. The forecasting approach achieves this task using the same functionality of the first component of the forecasting approach II introduced in Section 6.2.1.

Example ▷ The forecasting approach III constructs an ARIMA model for the general trend data constructed in P1 by first applying the K-S test and KPSS test to check for the normality and stationarity respectively. The forecasting approach concludes that the general trend data is not normally distributed; however, the transformation parameter of value "1.8" provides approximately normally distributed data which is referred as GT_t(TRT). In addition, it concludes that the data is not stationary, however, the differenced data (referred as GT_t(DTRT)) is stationary using the first difference.

The approach computes the ACF and PACF of the prepared data, GT_t(DTRT), which are plotted in Figure 6.8. From this Figure it can be seen that the ACF cuts off after 3 lags and the PACF decays. As a result, the initial identified order of the ARIMA model is $p = 0$ and $q = 3$, in addition to that $d = 1$. Based on the

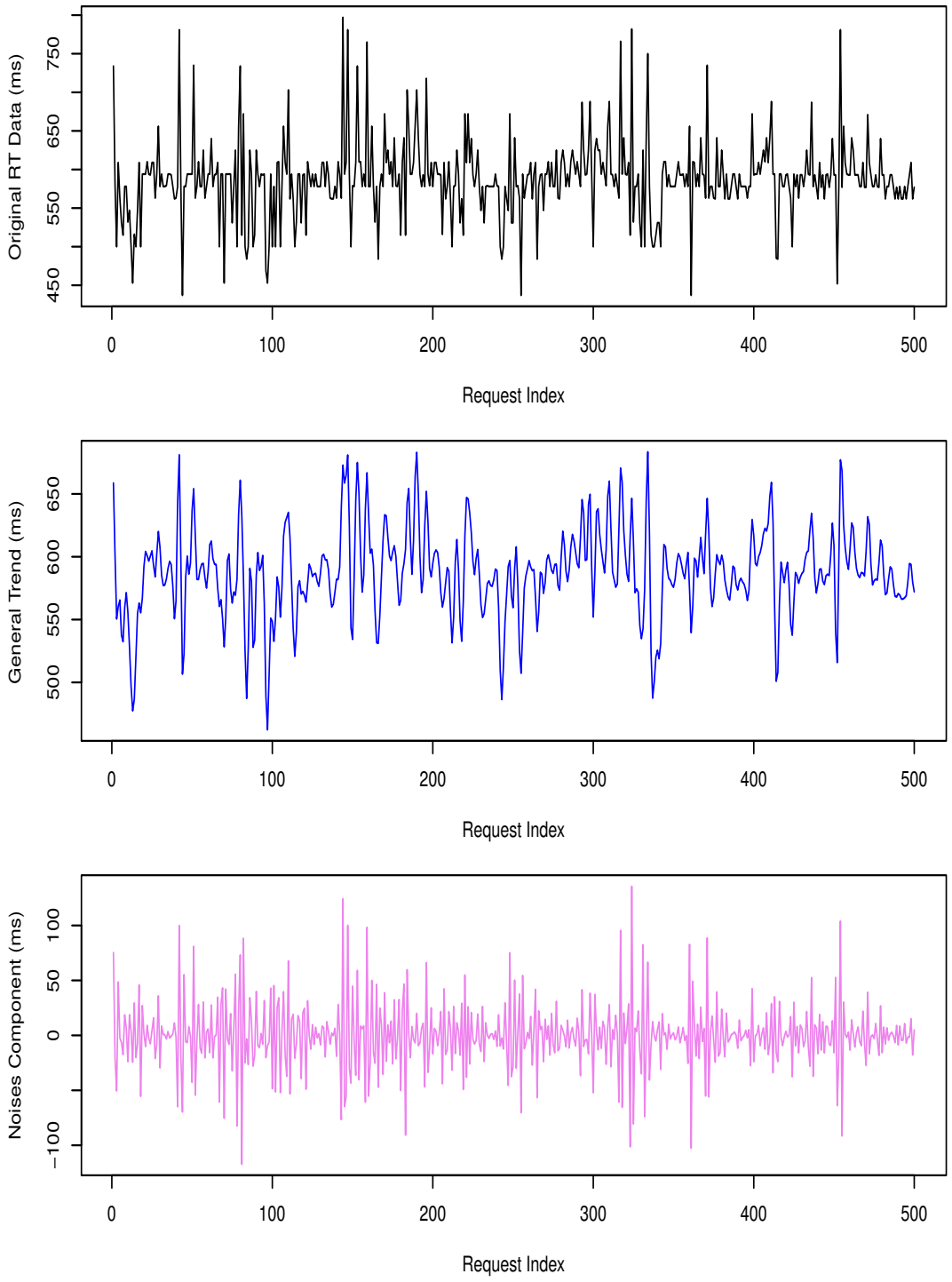


Figure 6.7: The original WS_2(RT) dataset and its constructed general trend and noises component sub-series

identified initial ARIMA model order and the under-fitting and over-fitting methods, the approach identifies fifteen ARIMA models for GT_t(DTRT) with the orders that are the combination of $p = 0, 1, 2$ and $q = 1, 2, 3, 4, 5$.

The forecasting approach uses the MLE method for each model to estimate the parameters and computes the t-test values and its p-values for all the estimates. After that, the approach checks the diagnostics and uses the AICc value to select the best ARIMA model that can be used to forecast the future values of GT_t(TRT). This model is ARIMA$(3, 1, 2)$, which its estimates are presented in Table 6.3. ◁

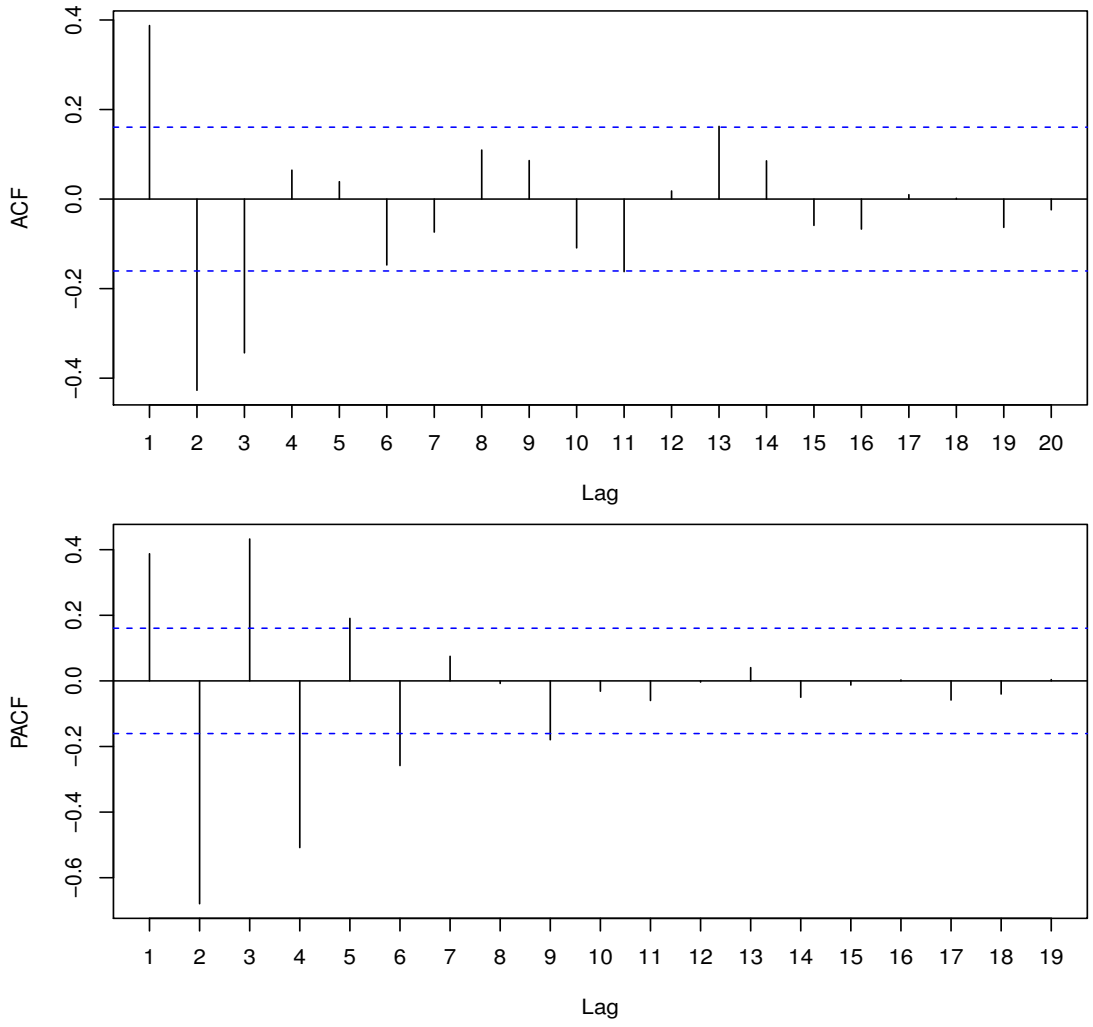


Figure 6.8: ACF and PACF values of GT_t(DTRT)

Parameter	Estimate	t-value	P-value
AR(1)	0.284	5.019	0.002
AR(2)	-0.636	-11.311	0.001
MA(1)	0.636	3.469	0.021
MA(2)	0.257	6.125	0.001

Table 6.3: Estimates of the best ARIMA model for GT_t(TRT)

6.3.2.2 (P4) Constructing ARIMA-GARCH Model for the Noises Component

In this phase, the forecasting approach III constructs an ARIMA-GARCH model for the noises component (NC_t). The forecasting approach achieves this task using the same functionality of the first and second components of the forecasting approach II introduced in Sections 6.2.1 and 6.2.2.

Example ▷ The forecasting approach III constructs an ARIMA-GARCH model for the noises component data constructed in P1 by first applying the K-S test and KPSS test to check for the normality and stationarity respectively. The forecasting approach concludes that the noises component data (referred as NC_t(RT)) is stationary and approximately normally distributed. The approach computes the ACF and PACF of the NC_t(RT) data as plotted in Figure 6.9, and finds that the ACF decays and the PACF cuts off after 2 lags. As a result, the approach identifies the initial order of the ARIMA model as $p = 2$ and $q = 0$, and identifies twelve ARIMA models for NC_t(RT) with the orders that are the combination of $p = 1, 2, 3, 4$ and $q = 0, 1, 2$. After that, the approach estimates the twelve identified ARIMA models using the MLE method, checks the diagnostics and uses the AICc value to select the best ARIMA model that can be used to forecast the future values of NC_t(RT). This model is ARIMA$(1, 0, 1)$, which its estimates are presented in Table 6.4.

To construct the GARCH model, the forecasting approach computes the squared residuals and their ACF and PACF which are plotted in Figure 6.10. Since the ACF

decays and the PACF cuts off after 2 lags, the approach identifies twelve GARCH models with the orders that are the combination of $r = 1, 2, 3, 4$ and $m = 0, 1, 2$. The approach estimates the twelve identified GARCH models using the MLE method, checks the diagnostics and selects GARCH$(1, 1)$ as the best GARCH model that can be used with ARIMA$(1, 0, 1)$ to forecast the future values of $\mathrm{NC}_t(\mathrm{RT})$. The estimates of GARCH$(1, 1)$ are presented in Table 6.5. ◁

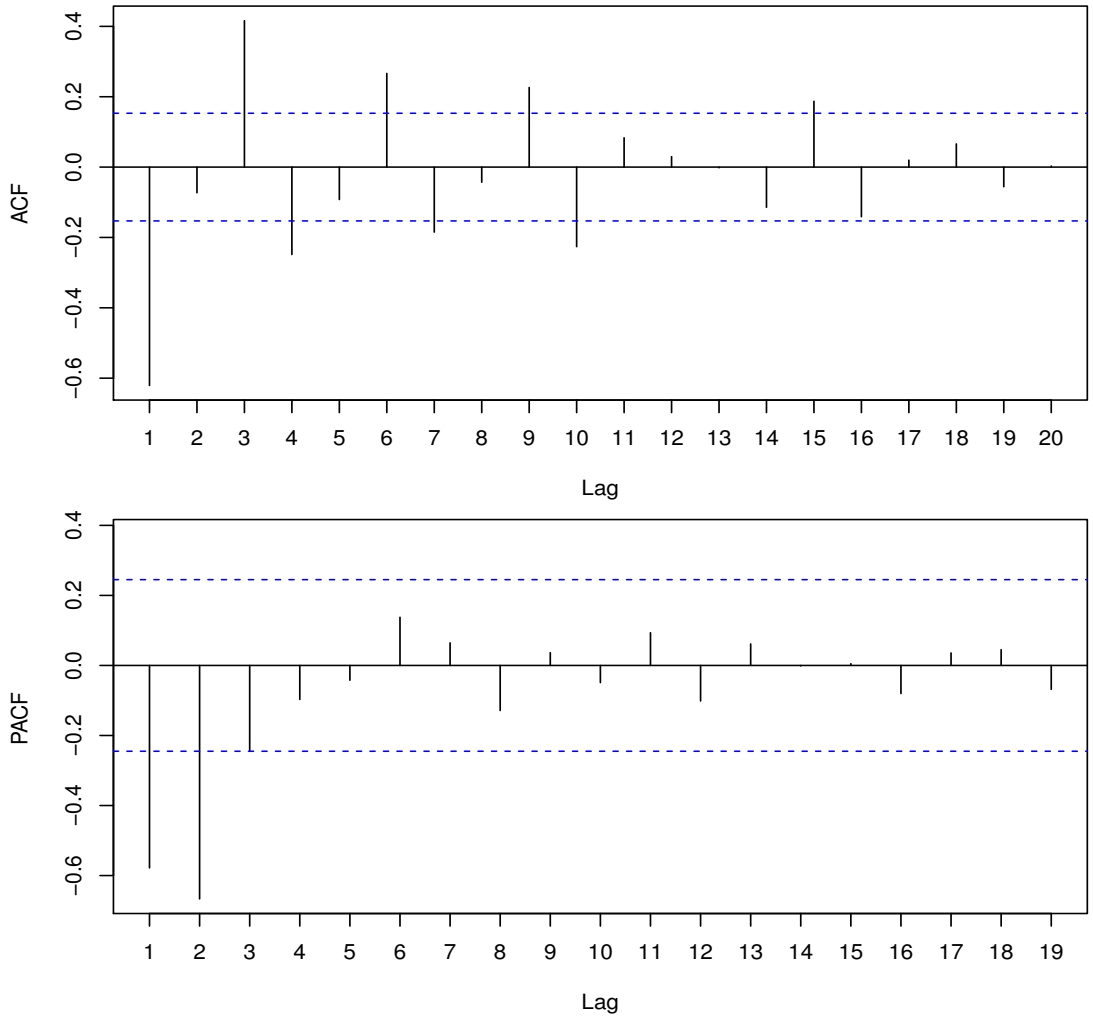


Figure 6.9: ACF and PACF values of $\mathrm{NC}_t(\mathrm{RT})$

Parameter	Estimate	t-value	P-value
AR(1)	-0.530	-7.581	0.001
MA(1)	-0.752	-45.484	0.000

Table 6.4: Estimates of the best ARIMA model for $NC_t(RT)$

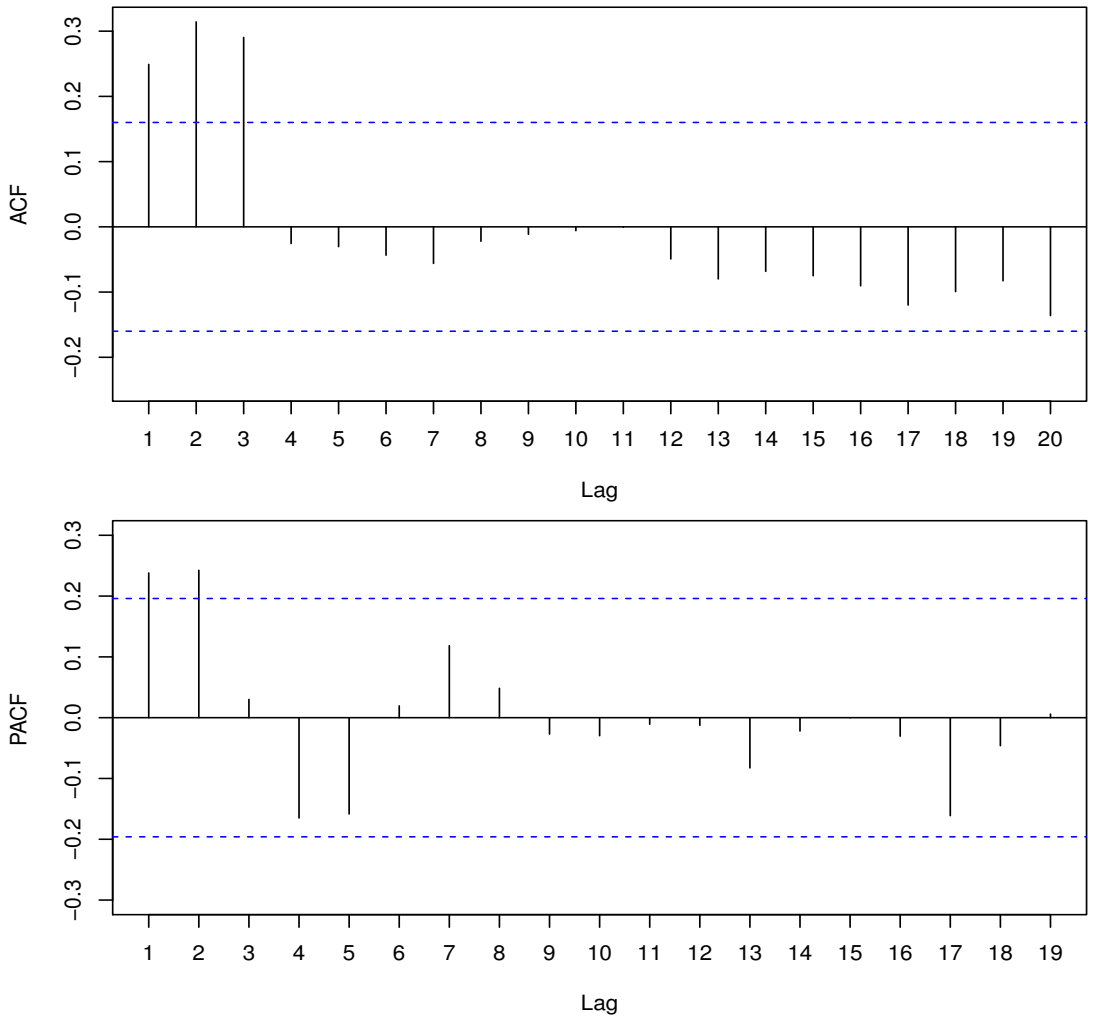


Figure 6.10: ACF and PACF values of the squared residuals of $NC_t(RT)$

Parameter	Estimate	t-value	P-value
ARCH(1)	0.563	3.415	0.001
GARCH(1)	0.385	3.984	0.000

Table 6.5: Estimates of the best GARCH model for the squared residuals of $\mathrm{NC}_t(\mathrm{RT})$

6.3.3 Continuously Forecasting Process

The main task of this component is to use the constructed ARIMA and ARIMA-GARCH models and the new obtained QoS data to continuously forecast the future QoS values and evaluate the adequacy and forecasting accuracy of the constructed models, which is achieved through two phases discussed as follows.

6.3.3.1 (P5) Computing Forecasts and Predictive Residuals

The forecasting approach uses the new obtained QoS data and the constructed ARIMA and ARIMA-GARCH models to continuously forecast the future values of the general trend GT_t and noises NC_t sub-series respectively. Then, the approach forecasts the future values of the given QoS data y_t by combining the forecasts of GT_t and NC_t sub-series. Simply, the one-step ahead forecast of y_t is computed as follows:

$$\hat{y}_{t+1} = \hat{GT}_{t+1} + \hat{NC}_{t+1} \tag{6.15}$$

where $\hat{GT}_{t+1}$ and $\hat{NC}_{t+1}$ are the one-step ahead forecasts of GT_t and NC_t sub-series respectively, and the predictive residuals are computed as:

$$\hat{\varepsilon}_t = (y_t - \hat{y}_t). \tag{6.16}$$

Example ▷ The forecasting approach uses the constructed ARIMA$(3,1,2)$ and ARIMA$(1,0,1)$-GARCH$(1,1)$ models to forecast the future values of the $\mathrm{GT}_t(\mathrm{RT})$ and $\mathrm{NC}_t(\mathrm{RT})$ datasets respectively. Then, by combing the forecasts of $\mathrm{GT}_t(\mathrm{RT})$ and $\mathrm{NC}_t(\mathrm{RT})$ the approach forecasts the future values of the $\mathrm{WS}_2(\mathrm{RT})$ dataset and computes the predictive residuals. The one-step-ahead forecasts of the last 100 observations of the $\mathrm{WS}_2(\mathrm{RT})$, $\mathrm{GT}_t(\mathrm{RT})$ and $\mathrm{NC}_t(\mathrm{RT})$ are depicted in Figure 6.11. ◁

6.3.3.2 (P6) Evaluating Adequacy and Forecasting Accuracy

Similarly to the forecasting approaches I and II, the forecasting approach III continuously evaluates the adequacy of the constructed ARIMA and ARIMA-GARCH models for the underlying QoS data using the CUSUM control chart and the forecasting accuracy using the MAPE measure.

In the case that the CUSUM control chart signals that the constructed ARIMA and ARIMA-GARCH models are not adequate any more for the underlying QoS data or the forecasting accuracy is very low based on the MAPE measure, the forecasting approach will re-construct other adequate ARIMA and ARIMA-GARCH models based on the new collected QoS data and the information obtained from the predictive residuals analysis.

Example ▷ The forecasting approach computes the upper and lower CUSUM statistics for the predictive residuals, as depicted in Figure 6.12, which do not exceed the decision interval and indicate that the used ARIMA$(3,1,2)$ and ARIMA$(1,0,1)$-GARCH$(1,1)$ models are still adequate for the underlying response time data. In addition, the MAPE measure is computed and its value is 3.76%, which is relatively small and indicates to be accepted forecasting accuracy. ◁

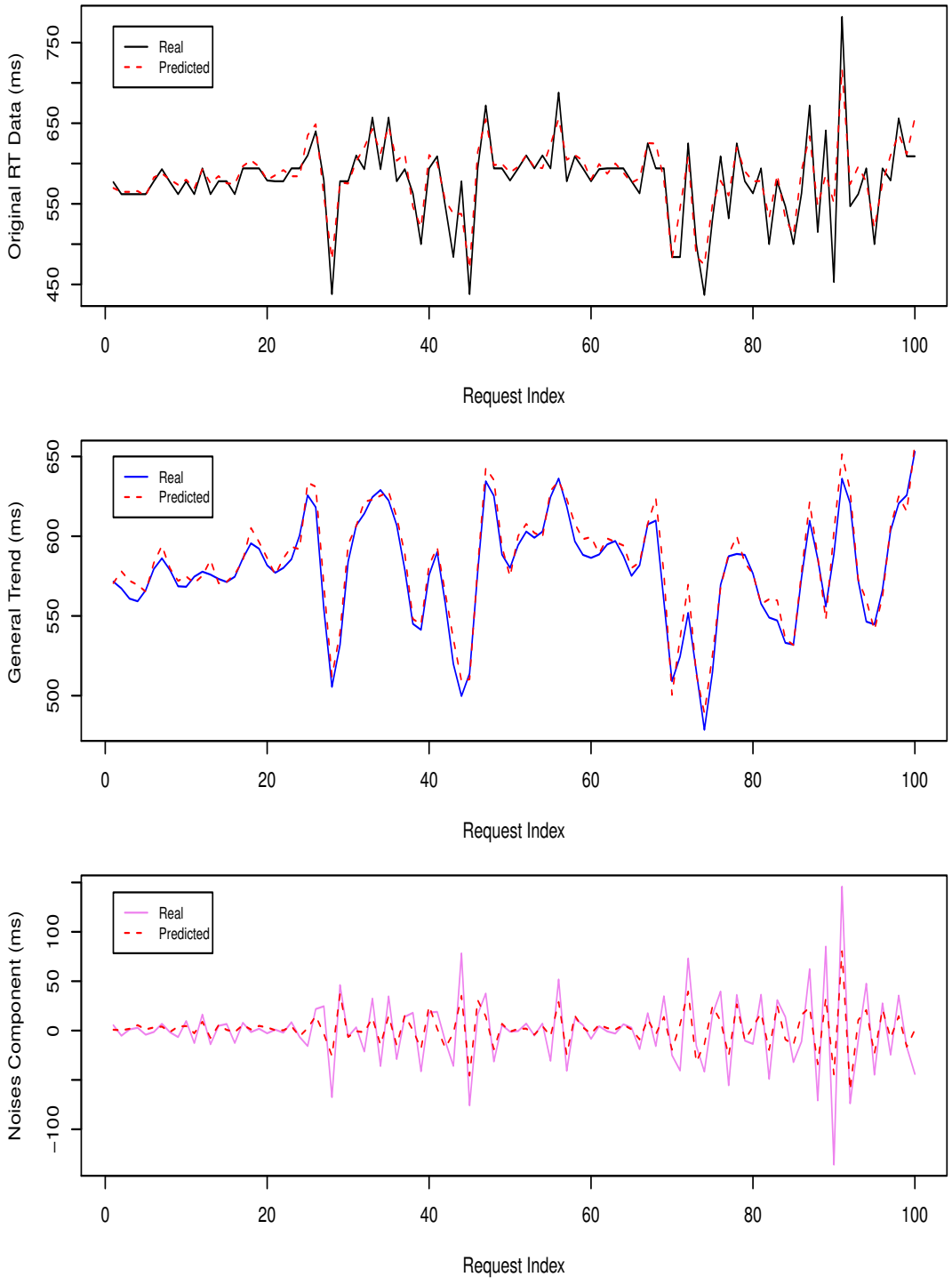


Figure 6.11: Real vs. predicted values of $WS_2(RT)$, $GT_t(RT)$ and $NC_t(RT)$

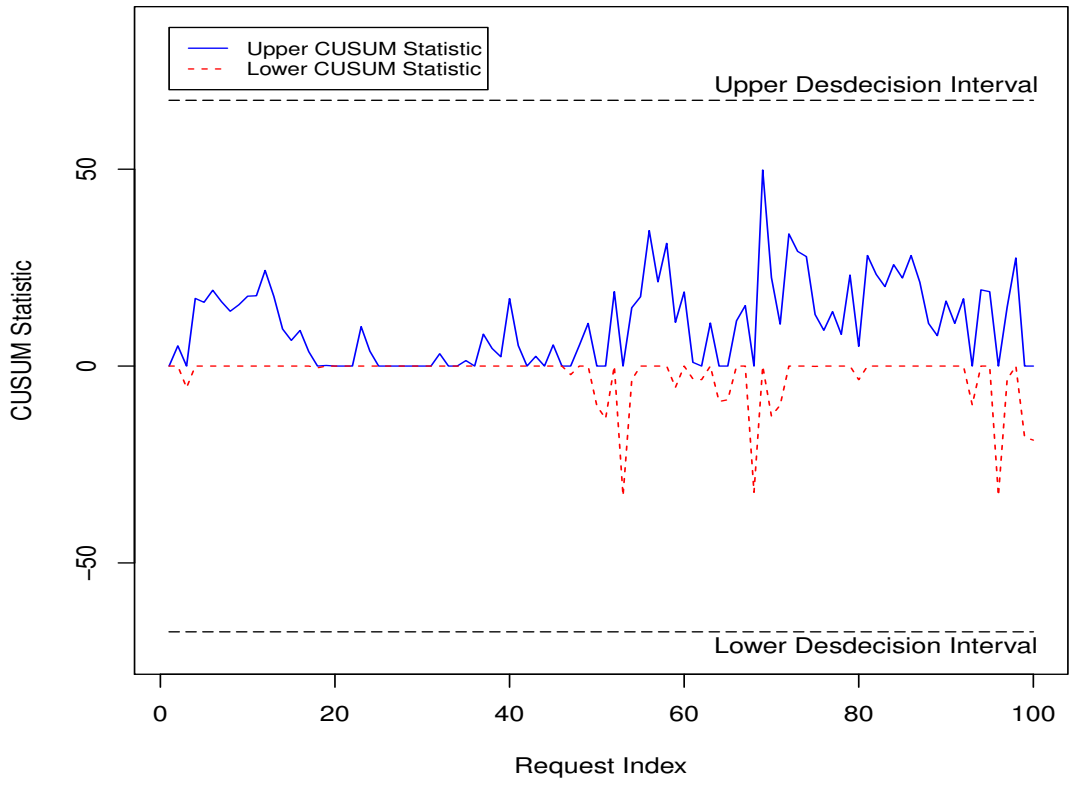


Figure 6.12: CUSUM statistics for the predictive residuals of WS_2(RT) for the forecasting approach III

6.4 Summary

In this chapter, we first summarized the background of the GARCH models and Wavelet Analysis. We then introduced the two proposed forecasting approaches II and III with a running example of response time of a real-world Web service. The forecasting approach II is based on ARIMA and GARCH models, while the forecasting approach III is based on wavelet analysis, ARIMA and GARCH models. These two forecasting approaches address the same problem of forecasting linearly dependent QoS attributes with volatility clustering. However, the accuracy and performance of these two forecasting approaches need to be evaluated in order to conclude to what extent they are equivalent and identify their relative preferences.

Chapter 7

Forecasting Approaches for Nonlinearly dependent QoS Attributes with Volatility Clustering

The previous two chapters address separately the problems of nonlinearity and volatility clustering of QoS attributes. Namely, Chapter 5 proposes the forecasting approach I based on the SETARMA models to forecasting the nonlinearly dependent QoS attributes with constant variance over time. In addition, Chapter 6 proposes the forecasting approach II based on the ARIMA and GARCH models and the forecasting approach III based on the wavelet analysis, ARIMA and GARCH models to forecasting the linearly dependent QoS attributes with volatility clustering. Consequently, the current chapter builds on the proposed forecasting approaches in order to address together the nonlinearity and volatility clustering of QoS attributes. This chapter proposes two forecasting approaches to model the nonlinearly dependent QoS attributes with volatility clustering and improve the forecasting accuracy.

The first forecasting approach, which is called forecasting approach IV, is proposed based on SETARMA and GARCH models. On the other hand, the second

forecasting approach, which is called forecasting approach V, is proposed based on the wavelet analysis, SETARMA and GARCH models. These two forecasting approaches are introduced with a running example in the rest of this chapter.

7.1 Forecasting Approach IV Based on SETARMA and GARCH Models

The proposed forecasting approach IV integrates SETARMA and GARCH models to capture the nonlinearity and volatility clustering of QoS attributes and accurately forecast future QoS values. In brief summary, the forecasting approach first constructs a SETARMA model for the given QoS data, computes the squared residuals which include the volatility clustering, and constructs a GARCH model. After that, the forecasting approach, by using the new obtained QoS data, continuously updates the constructed SETARMA-GARCH model, computes the QoS forecasts and evaluates the adequacy and forecasting accuracy of the constructed SETARMA-GARCH model. Consequently, this forecasting approach consists of three components: SETARMA model construction process, GARCH model construction process, and continuously forecasting process; as explained in Figure 7.1. In the following the proposed forecasting approach is introduced and explained by a running example of the response time dataset (which is referred as $WS_3(RT)$) of the web service "ChinaStockWebService"[1] which reports timely chinese stock market data, e.g. stock name, price, ...etc.

7.1.1 SETARMA Model Construction Process

The main task of this component is to construct the SETARMA model for the given QoS data. The forecasting approach IV achieves this task using the same functionality of the first component of the forecasting approach I introduced in Chapter 5 in Section 5.2.1. Briefly, the forecasting approach IV constructs the

[1] `http://www.webxml.com.cn/WebServices/ChinaStockWebService.asmx`

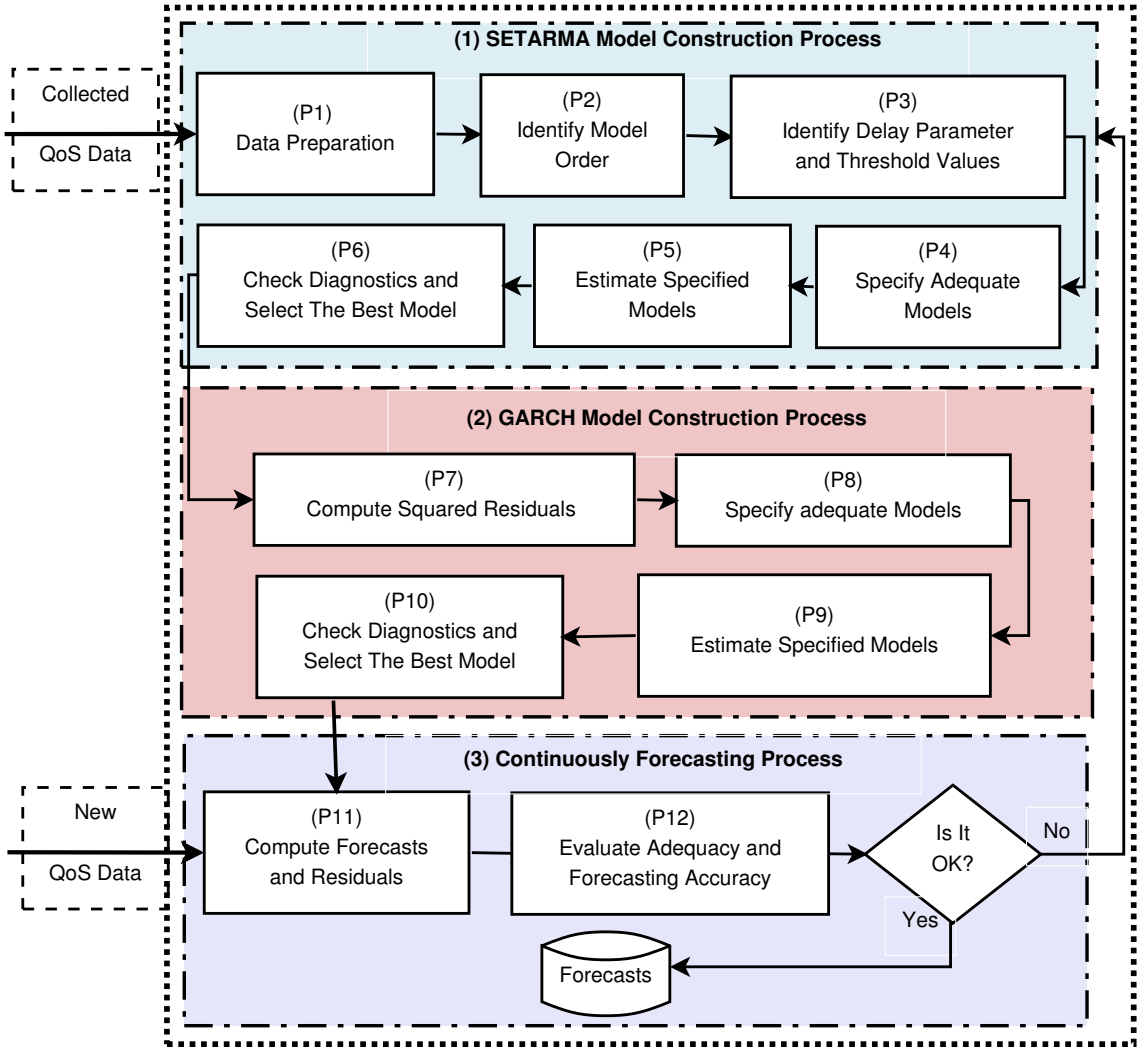


Figure 7.1: The proposed forecasting approach IV based on SETARMA and GARCH models

SETARMA model for the given QoS data through six phases:

(P1) Data preparation: The forecasting approach prepares the QoS by checking the serial dependency, normality and stationarity using the runs test [77], Kolmogorov-Smirnov (K-S) test [77] and KPSS test [115], respectively. In addition, the approach uses the Box-Cox transformations [32] and differencing method to achieve the normality and stationarity, respectively.

(P2) Initial SETARMA model order identification: Using the autocorrelation function (ACF) and the partial autocorrelation function (PACF) [33] of the given

QoS data, the forecasting approach identifies an initial order for the SETARMA model.

(P3) Delay parameter and thresholds identification: Using the Hansen test [90], the forecasting approach identifies the values of the delay parameter and thresholds for the SETARMA model.

(P4) Adequate models specification: The forecasting approach specifies a combination of adequate SETARMA models for the given QoS data based on the dependency structure, in terms of the ACF and PACF, and under-fitting and over-fitting methods.

(P5) SETARMA models estimation: The forecasting approach estimates the parameters of the specified adequate models in P4 to provide the best fit for the given QoS data using the conditional least squares (CLS) estimation method [227].

(P6) SETARMA models checking and the best model selection: The forecasting approach checks the diagnostics of the SETARMA models to identify whether they are satisfied, and these diagnostics include the estimates significance test, satisfaction of the stationarity and invertibility conditions and residuals randomness. If one or more diagnostics are not satisfied, the current SETARMA model is inadequate and it is necessary to be removed from the set of models specified in P4.

Example ▷ The forecasting approach IV constructs a SETARMA model for the WS_3(RT) data by first applying the runs test, K-S test and KPSS test to check for the serial dependency, normality and stationarity respectively. The forecasting approach concludes that the WS_3(RT) data is serially dependent and stationary, but not normally distributed; however, the transformation parameter of value "0.322" provides approximately normally distributed data which is referred as the WS_3(TRT).

The approach computes the ACF and PACF of the prepared data, WS_3(TRT), which are plotted in Figure 7.2. From this Figure it can be seen that the ACF

decays and the PACF cuts off after 2 lags. As a result, the initial identified order of the SETARMA model is $p = 2$ and $q = 0$. In addition, the approach runs the Hansen test two times with inputs ($p = 2$ and $d_p = 1$) and ($p = 2$ and $d_p = 2$) and based on the output identifies that the delay parameter $d_p = 1$ and the threshold value is 1530. Based on the identified initial SETARMA model order and the under-fitting and over-fitting methods, the approach identifies twelve SETARMA models for WS_3(TRT) with the orders that are the combination of $p = 1, 2, 3, 4$ and $q = 0, 1, 2$.

The forecasting approach uses the CLS method for each model to estimate the parameters and computes the t-test values and its p-values for all the estimates. After that, the approach checks the diagnostics and uses the AICc value to select the best SETARMA model that can be used to forecast the future values of WS_3(TRT). This model is SETARMA$(2, 3, 0)$, which its estimates are presented in Table 7.1. ◁

Regime	Parameter	Estimate	t-value	P-value
Low	SETAR(1)	0.194	6.252	0.001
	SETAR(2)	0.149	3.621	0.026
	SETAR(3)	0.055	2.150	0.042
High	SETAR(1)	0.164	3.318	0.001
	SETAR(2)	0.183	3.822	0.000
	SETAR(3)	0.202	0.047	0.000

Table 7.1: Estimates of the best SETARMA model for WS_3(TRT)

7.1.2 GARCH Model Construction Process

This component uses the residuals of the constructed SETARMA model to construct the GARCH model. The forecasting approach IV achieves this task using the same functionality of the second component of the forecasting approach II introduced in

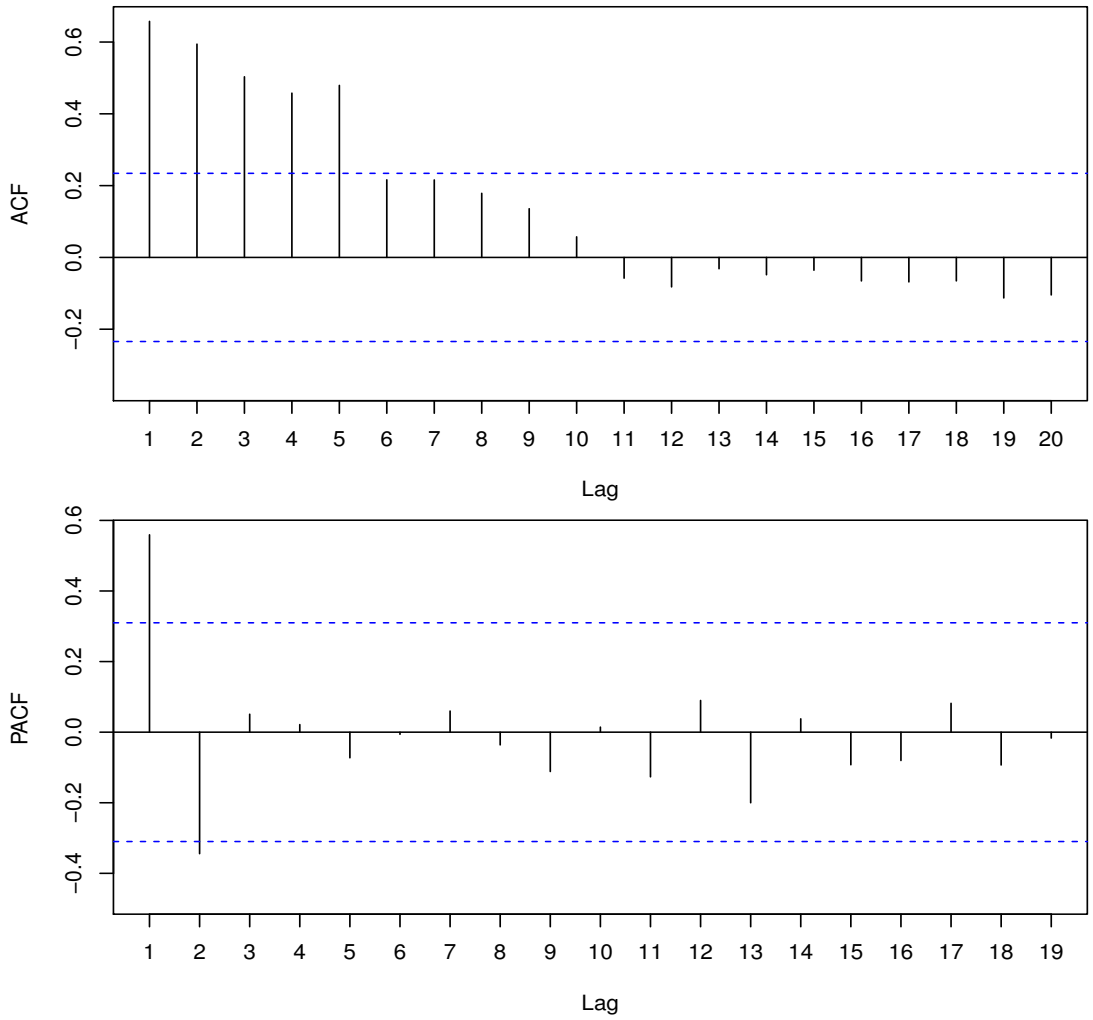


Figure 7.2: ACF and PACF values of WS_3(TRT)

Chapter 6 in Section 6.2.2. Briefly, the forecasting approach constructs the GARCH model through four phases:

(P7) Computing squared residuals: The forecasting approach uses the constructed SETARMA model to compute the squared residuals.

(P8) Adequate GARCH models specification: Using the ACF and the PACF of the computed squared residuals, the forecasting approach identifies an adequate GARCH models.

(P9) GARCH models estimation: The forecasting approach estimates the parameters of the specified adequate GARCH models in P8 using the maximum likelihood estimation method [227].

(P10) GARCH models checking and the best model selection: The forecasting approach checks the diagnostics of the GARCH models which include the estimates significance test, fulfilment of the GARCH model constraints (which are presented in equation 6.3 in Chapter 6) and residuals randomness. If one or more diagnostics are not satisfied, the current GARCH model is inadequate and it is necessary to be removed from the set of models specified in P8.

Example ▷ The forecasting approach computes the squared residuals and their ACF and PACF which are plotted in Figure 7.3. Since the ACF decays and PACF cuts off after 2 lags, the approach identifies the initial order of the GARCH model as $r = 2$ and $m = 0$.

Based on the identified initial GARCH model order and the under-fitting and over-fitting methods, the forecasting approach identifies twelve GARCH models with the orders that are the combination of $r = 1, 2, 3, 4$ and $m = 0, 1, 2$. The approach estimates the twelve identified GARCH models using the MLE method, checks the diagnostics and selects GARCH$(1, 1)$ as the best GARCH model that can be used with SETARMA$(2, 3, 0)$ to forecast the future values of WS_3(TRT). The estimates of GARCH$(1, 1)$ are presented in Table 7.2. ◁

Parameter	Estimate	t-value	P-value
ARCH(1)	0.155	2.983	0.003
GARCH(1)	0.804	15.638	0.000

Table 7.2: Estimates of the best GARCH model for the squared residuals of WS_3(TRT)

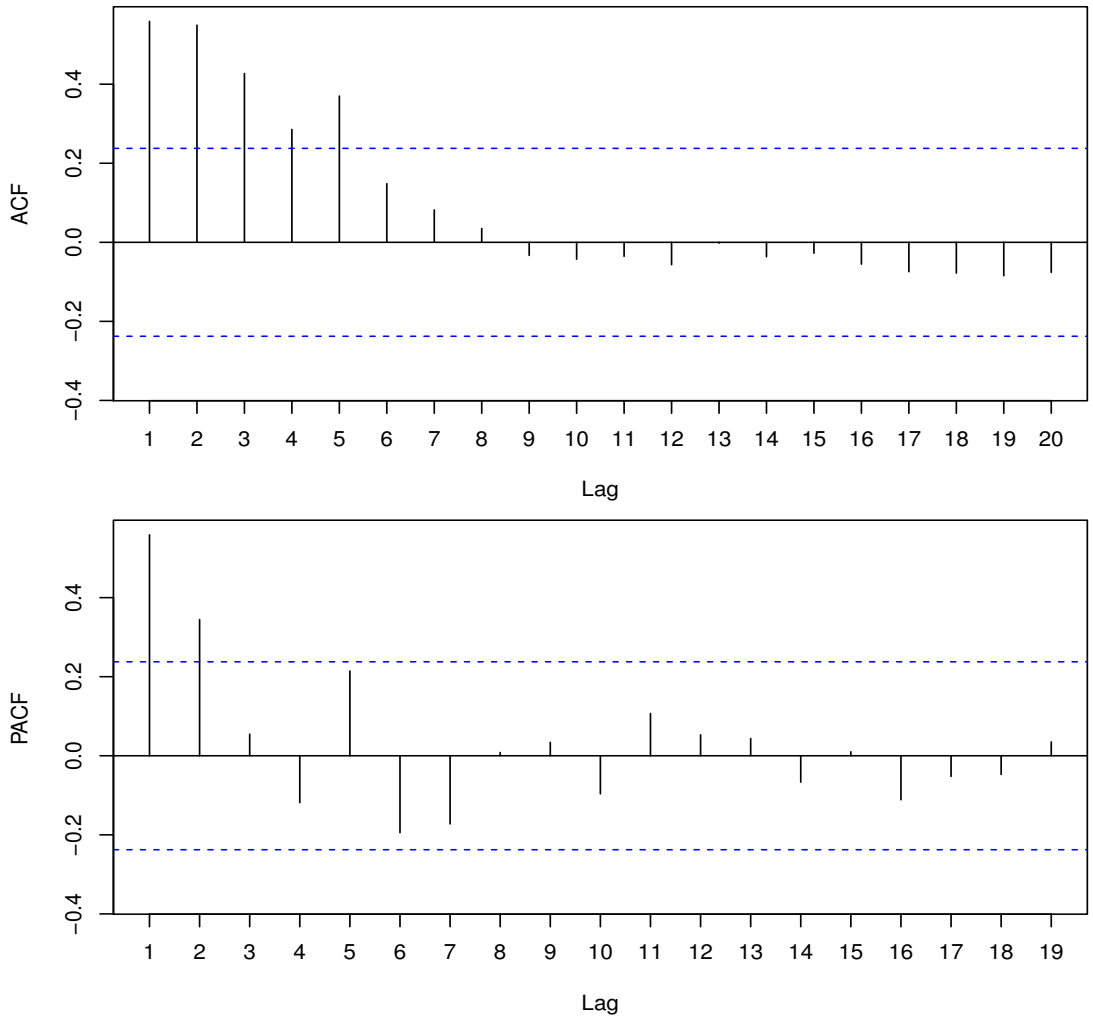


Figure 7.3: ACF and PACF values of the squared residuals of WS_3(TRT)

7.1.3 Continuously Forecasting Process

The forecasting approach IV uses the constructed SETARMA-GARCH model and the new obtained QoS data to continuously forecast the future QoS values and evaluate the adequacy and forecasting accuracy of the constructed SETARMA-GARCH model. The forecasting approach achieves this task using the same functionality of the second component of the forecasting approach I introduced in Chapter 5 in Section 5.2.2, which includes:

(P11) Computing forecasts and predictive residuals: The forecasting approach

uses the new obtained QoS data to continuously update the constructed SETARMA-GARCH model and thus compute the predictive residuals.

(P12) Evaluating adequacy and forecasting accuracy of SETARMA-GARCH model: The forecasting approach continuously evaluates the adequacy of the constructed SETARMA-GARCH model by using the CUSUM control chart [174] to monitor the predictive residuals. In addition, the forecasting approach evaluates the forecasting accuracy by computing the mean absolute percentage errors (MAPE) measure. In the case that the CUSUM control chart signals that the used SETARMA-GARCH model is not adequate any more for the underlying QoS data or the forecasting accuracy is very low based on the MAPE measure, the forecasting approach will return back to the first component to re-identify and construct other adequate SETARMA-GARCH model.

Example ▷ The forecasting approach uses the constructed SETARMA(2,3,0)-GARCH(1,1) model to forecast the future values of WS_3(RT), and the one-step-ahead forecasts of the last 100 observations and their predictive residuals are depicted in Figure 7.4. In addition, the CUSUM statistics for the predictive residuals are computed and depicted in Figure 7.5. It is clear from this Figure that the upper and lower CUSUM statistics do not exceed the decision interval, which indicates that the used SETARMA(2,3,0)-GARCH(1,1) model is still adequate for the underlying response time data. In addition, the MAPE measure is computed and its value is 7.18%, which is relatively small and indicates to be accepted forecasting accuracy. ◁

7.2 Forecasting Approach V Based on Wavelet Analysis, SETARMA and GARCH Models

The proposed forecasting approach V integrates wavelet analysis, SETARMA and GARCH models to decompose the complicated behavior of the given QoS data

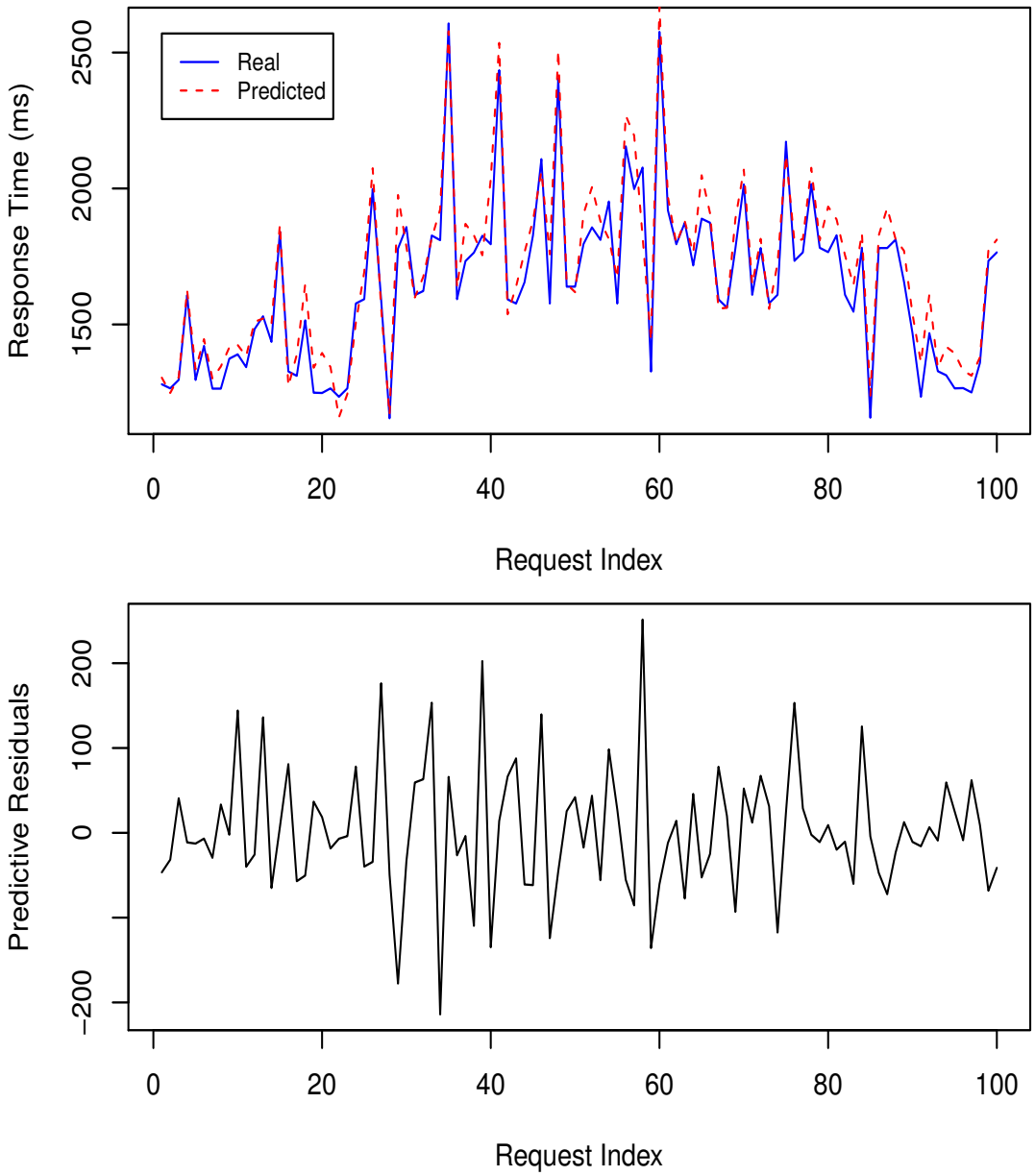


Figure 7.4: Real vs. predicted values of $WS_3(RT)$ and their predictive residuals for the forecasting approach IV

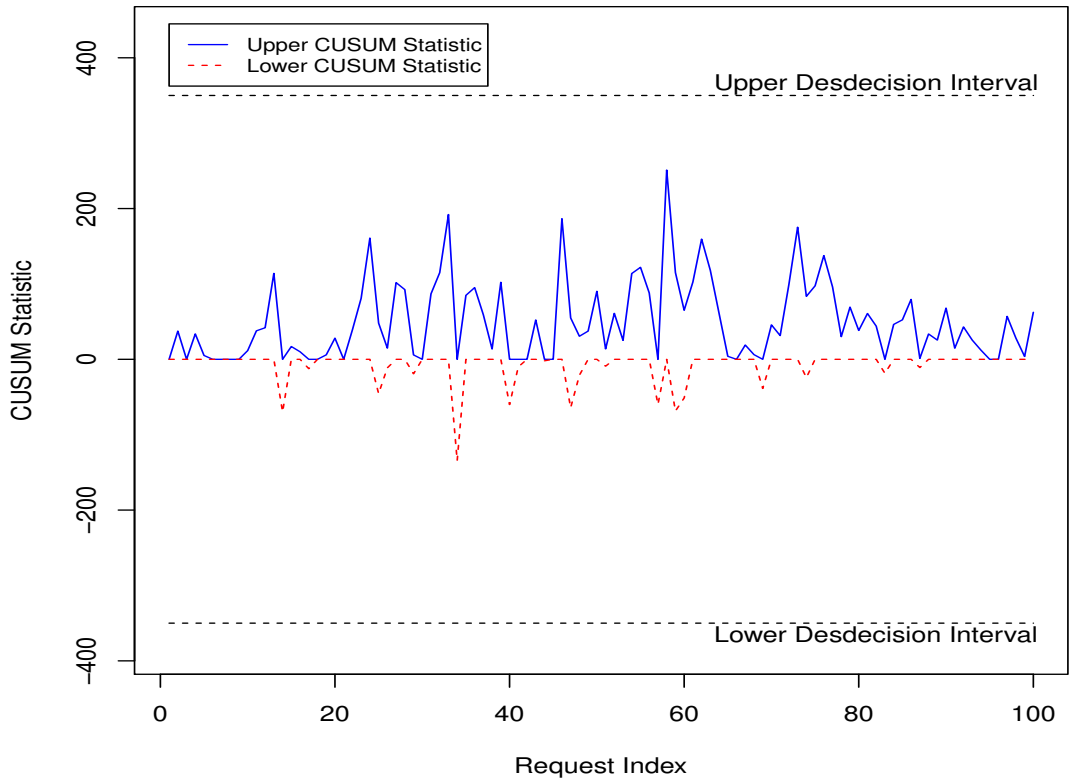


Figure 7.5: CUSUM statistics for the predictive residuals of WS_3(RT) for the forecasting approach IV

into two simplified sub-series to be able to capture the nonlinearity and volatility clustering of QoS attributes and provide accurate QoS forecasting.

In brief summary, the forecasting approach V first decomposes the complicated behavior of the given QoS data using wavelet analysis into two simplified sub-series: the general trend, which is purified from the volatility clustering, and the noises component, which includes the volatility clustering. Second, the forecasting approach constructs a SETARMA model for the general trend and a SETARMA-GARCH model for the noises component. Third, the forecasting approach, by using the new obtained QoS data, continuously updates the constructed SETARMA and SETARMA-GARCH models, computes the forecasts of the general trend and

noises component respectively, combines these forecasts to provide the original QoS forecasts, and evaluates the adequacy and forecasting accuracy of the constructed model.

Consequently, this forecasting approach consists of three components: Wavelet-based QoS time series decomposition, SETARMA and SETARMA-GARCH models construction process for the general trend and noises sub-series respectively, and continuously forecasting process; as explained in Figure 7.6. In the following the proposed forecasting approach is introduced and explained by a running example of the same response time dataset used in Section 7.1.

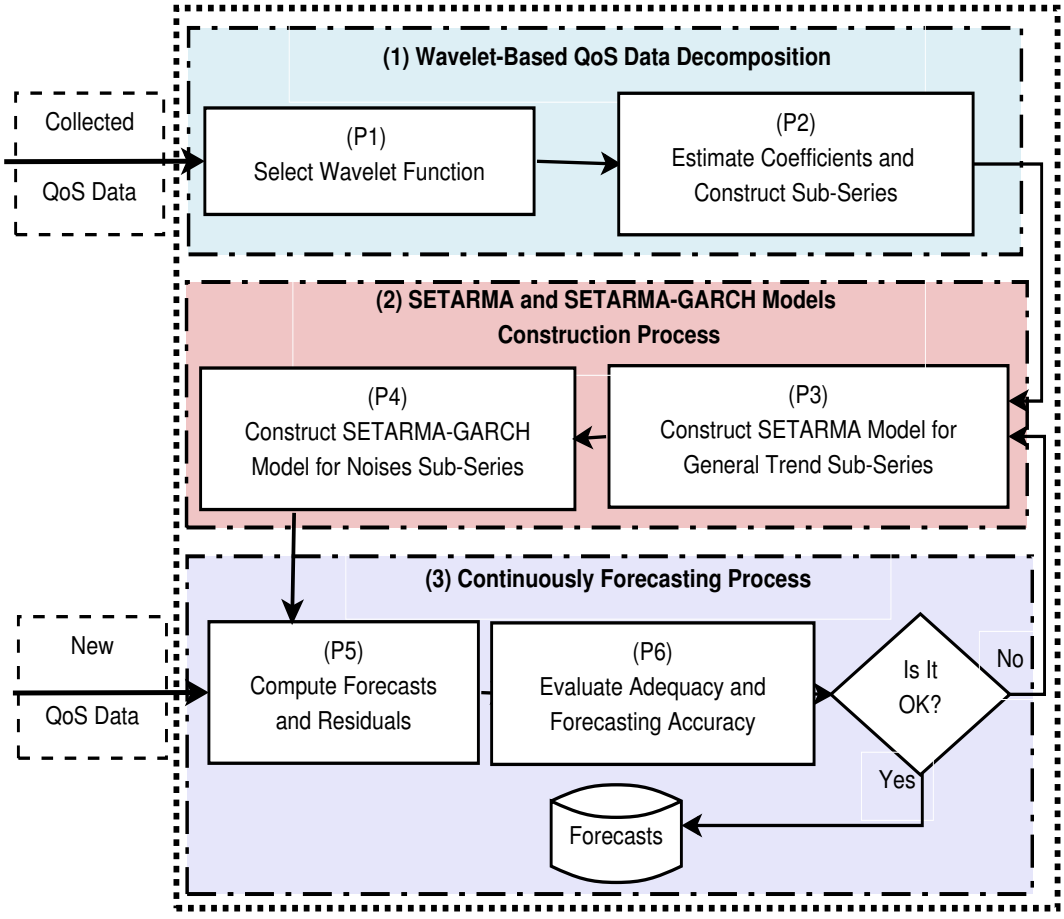


Figure 7.6: The proposed forecasting approach V based on Wavelet analysis, SETARMA and GARCH models

7.2.1 Wavelet-Based QoS Time Series Decomposition

This component uses wavelet analysis to decompose the given QoS data into the general trend GT_t and noises component NC_t sub-series by using the same functionality of the first component of the forecasting approach III introduced in Chapter 6 in Section 6.3.1. Briefly, the forecasting approach first adopts the Daubechies wavelet [57] and estimates its father $\varphi(t)$ and mother $\psi(t)$ functions. Then, the approach computes the decomposition coefficients and constructs the general trend GT_t and noises component NC_t sub-series.

Example ▷ The forecasting approach V uses the wavelet analysis to decompose the WS_3(RT) dataset into the general trend and noises component sub-series. The WS_3(RT) dataset and the constructed general trend and noises component sub-series are depicted in Figure 7.7. ◁

7.2.2 SETARMA and SETARMA-GARCH Models Construction Process

The main task of this component is to construct a SETARMA model for the general trend GT_t and a SETARMA-GARCH model for the noises component NC_t through two phases as follows.

7.2.2.1 (P3) Constructing SETARMA Model for the General Trend

In this phase, the forecasting approach V constructs a SETARMA model for the general trend GT_t using the same functionality of the first component of the forecasting approach IV introduced in Section 7.1.1.

Example ▷ The forecasting approach V constructs a SETARMA model for the general trend data GT_t(RT), and concludes that the SETARMA$(2, 2, 0)$ is the best SETARMA model that can be used to forecast the future values of GT_t(RT). The estimates of SETARMA$(2, 2, 0)$ are presented in Table 7.3 ◁

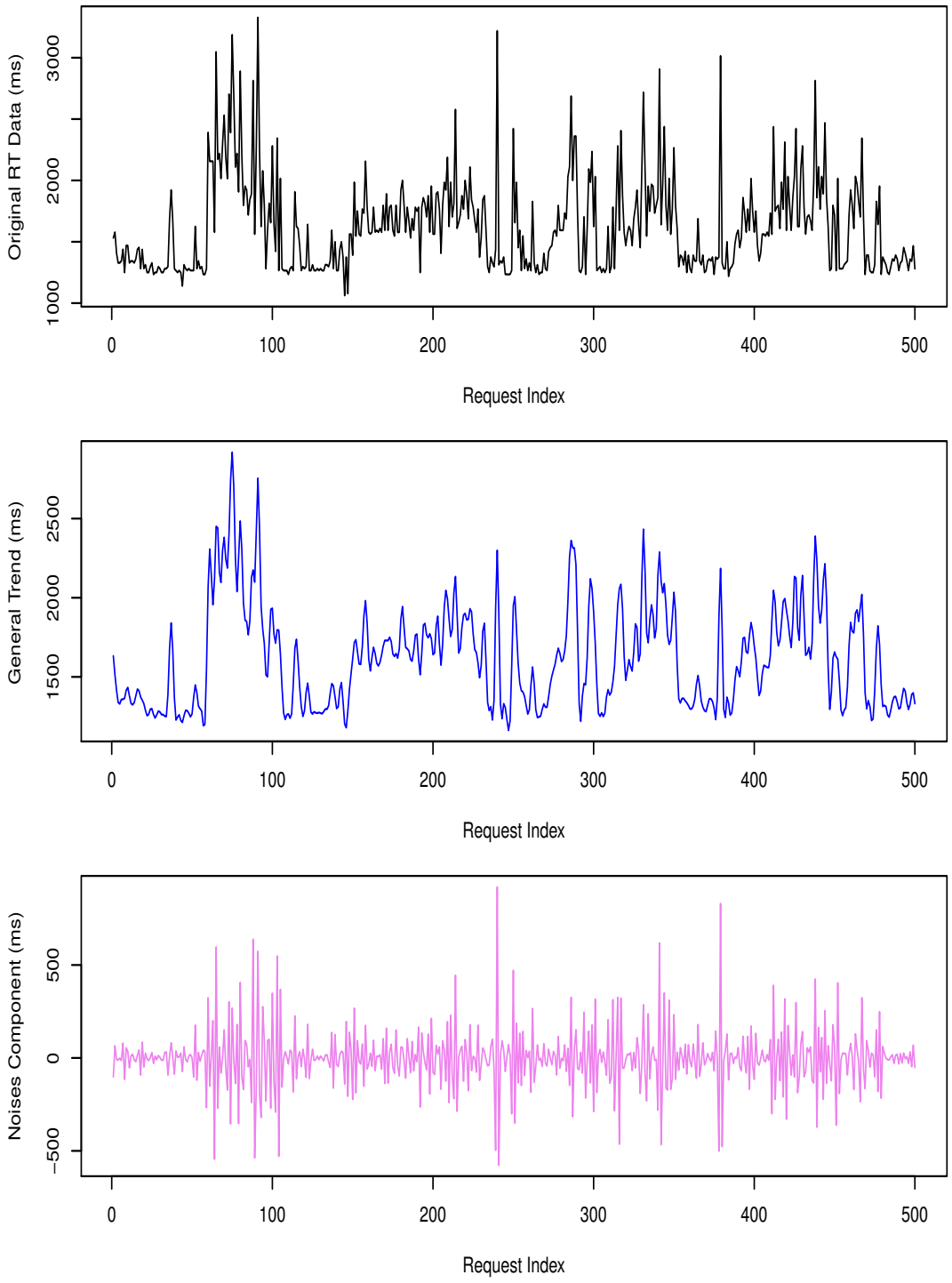


Figure 7.7: The original WS_3(RT) dataset and its constructed general trend and noises component sub-series

Regime	Parameter	Estimate	t-value	P-value
Low	SETAR(1)	0.415	1.982	0.043
	SETAR(2)	0.176	2.240	0.025
High	SETAR(1)	0.172	3.344	0.001
	SETAR(2)	0.232	4.919	0.000

Table 7.3: Estimates of the best SETARMA model for $\mathrm{GT}_t(\mathrm{RT})$

7.2.2.2 (P4) Constructing SETARMA-GARCH Model for the Noises Component

In this phase, the forecasting approach V constructs a SETARMA-GARCH model for the noises component NC_t using the same functionality of the first and second components of the forecasting approach IV introduced in Sections 7.1.1 and 7.1.2.

Example ▷ The forecasting approach V constructs a SETARMA-GARCH model for the noises component data $\mathrm{NC}_t(\mathrm{RT})$, and concludes that the SETARMA$(2, 2, 0)$-GARCH$(1, 1)$ is the best model that can be used to forecast the future values of $\mathrm{NC}_t(\mathrm{RT})$. The estimates of SETARMA$(2, 2, 0)$-GARCH$(1, 1)$ are presented in Tables 7.4 and 7.5. ◁

Regime	Parameter	Estimate	t-value	P-value
Low	SETAR(1)	-0.394	-23.588	0.000
	SETAR(2)	-0.249	-7.426	0.000
High	SETAR(1)	-0.635	-31.298	0.000
	SETAR(2)	-0.346	-20.434	0.000

Table 7.4: Estimates of the best SETARMA model for $\mathrm{NC}_t(\mathrm{RT})$

7.2.3 Continuously Forecasting Process

The forecasting approach V uses the constructed SETARMA and SETARMA-GARCH models and the new obtained QoS data to continuously forecast the future

Parameter	Estimate	t-value	P-value
ARCH(1)	0.465	3.571	0.000
ARCH(2)	0.455	4.477	0.000

Table 7.5: Estimates of the best GARCH model for the squared residuals of $\mathrm{NC}_t(\mathrm{RT})$

QoS values and evaluate the adequacy and forecasting accuracy of the constructed SETARMA and SETARMA-GARCH models. The forecasting approach achieves this task using the same functionality of the third component of the forecasting approach II introduced in Chapter 6 in Section 6.3.3, which includes:

(P5) Computing forecasts and predictive residuals: The forecasting approach uses the new obtained QoS data and the constructed SETARMA and SETARMA-GARCH models to continuously forecast the future values of the general trend GT_t and noises NC_t sub-series respectively. Then, the approach forecasts the future values of the given QoS data by combining the forecasts of GT_t and NC_t sub-series, and computes the predictive residuals.

(P6) Evaluating adequacy and forecasting accuracy of SETARMA and SETARMA-GARCH models: The forecasting approach continuously evaluates the adequacy of the constructed SETARMA and SETARMA-GARCH models by using the CUSUM control chart [174] to monitor the predictive residuals. In addition, the forecasting approach evaluates the forecasting accuracy by computing the mean absolute percentage errors (MAPE) measure. In the case that the CUSUM control chart signals that the used SETARMA and SETARMA-GARCH models are not adequate any more for the underlying QoS data or the forecasting accuracy is very low based on the MAPE measure, the forecasting approach will re-construct other adequate SETARMA and SETARMA-GARCH models.

Example ▷ The forecasting approach uses the constructed SETARMA$(2, 2, 0)$ and SETARMA$(2, 2, 0)$-GARCH$(2, 0)$ models to forecast the future values of the

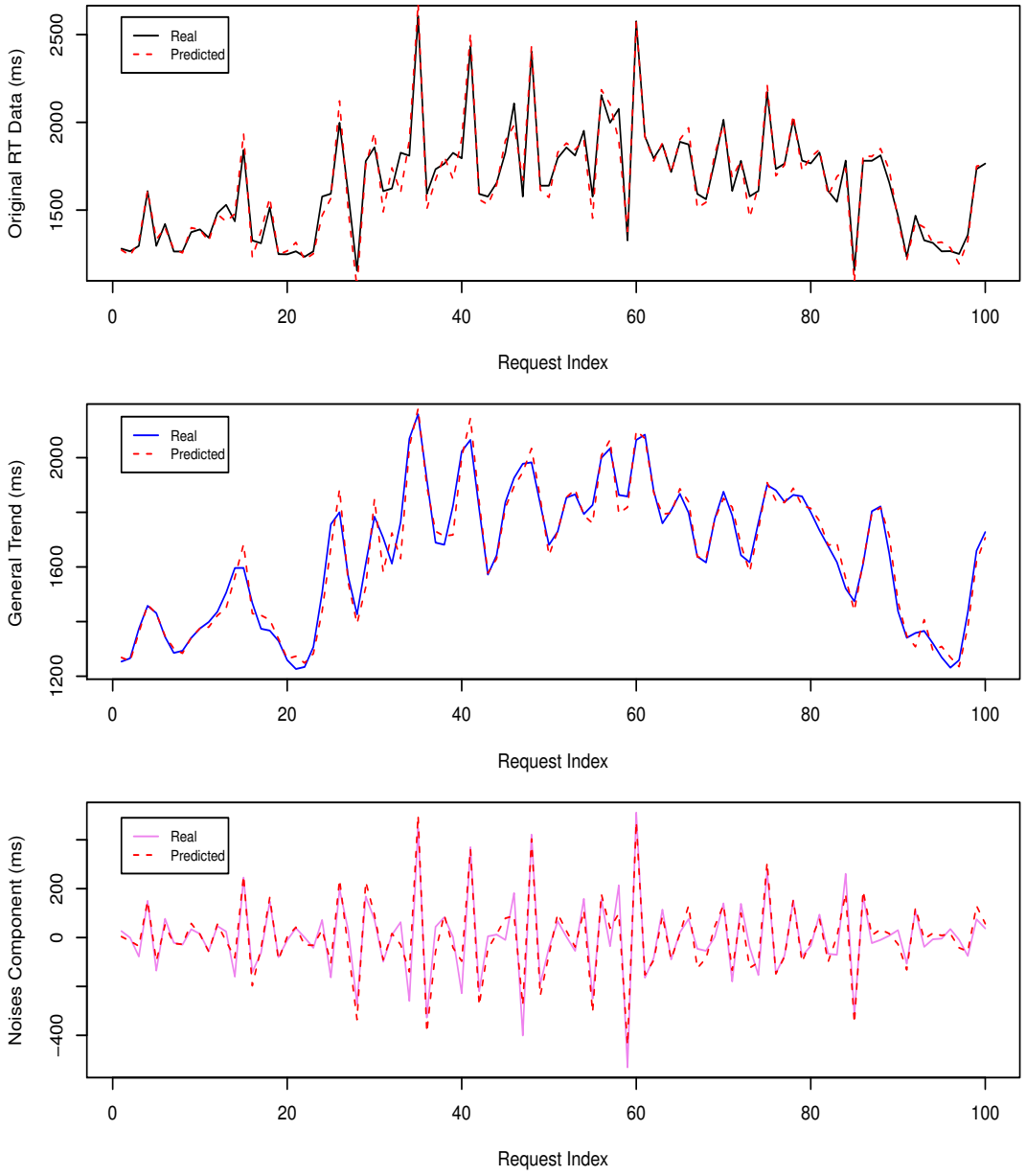


Figure 7.8: Real vs. predicted values of $WS_3(RT)$ and their predictive residuals for the forecasting approach V

$GT_t(RT)$ and $NC_t(RT)$ datasets respectively. Then, by combing the forecasts of $GT_t(RT)$ and $NC_t(RT)$ the approach forecasts the future values of the $WS_3(RT)$ dataset and computes the predictive residuals. The one-step-ahead forecasts of the last 100 observations of the $WS_3(RT)$, $GT_t(RT)$ and $NC_t(RT)$ are depicted in Figure 7.8. In addition, the CUSUM statistics for the predictive residuals are computed and depicted in Figure 7.9. It is clear from this Figure that the upper and lower CUSUM statistics do not exceed the decision interval, which indicates that the used models is still adequate for the underlying response time data. In addition, the MAPE measure is computed and its value is 5.52%, which is relatively small and indicates to accepted forecasting accuracy. ◁

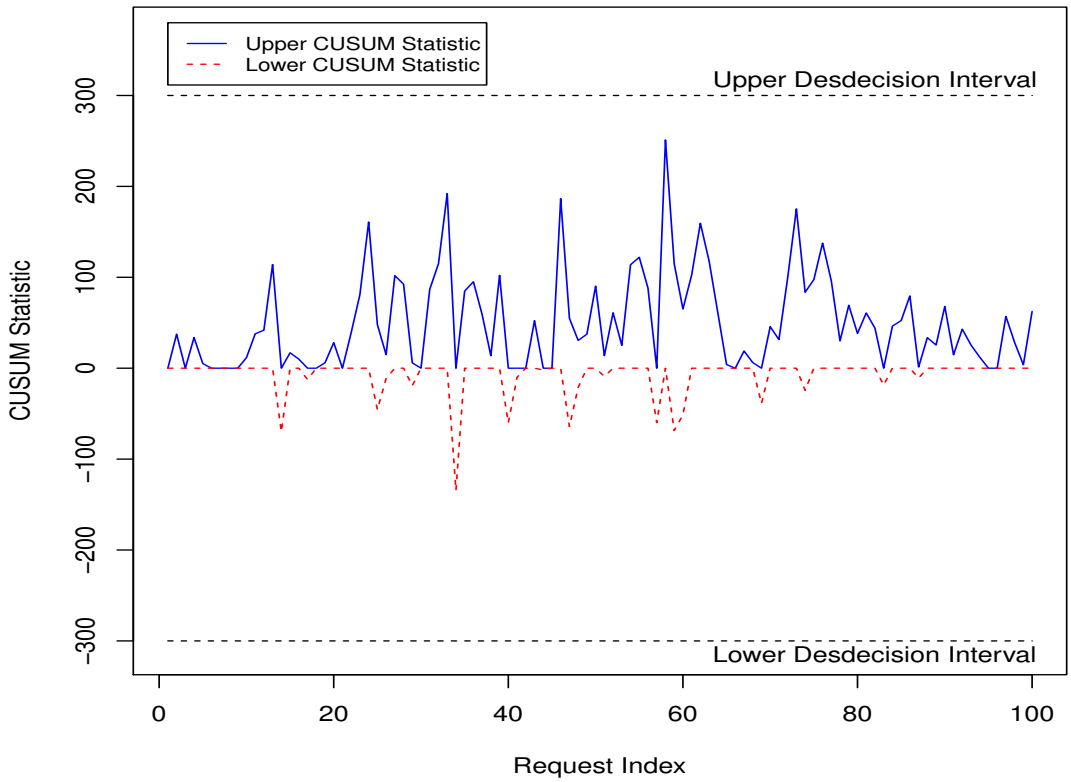


Figure 7.9: CUSUM statistics for the predictive residuals of $WS_3(RT)$ for the forecasting approach V

7.3 Summary

In this chapter, we introduced the two proposed forecasting approaches IV and V with a running example of response time of a real-world Web service. These two forecasting approaches build on the proposed forecasting approaches in previous chapters in order to address together the nonlinearity and volatility clustering of QoS attributes and improve the forecasting accuracy. The forecasting approach IV is based on the SETARMA and GARCH models, while the forecasting approach V is based on the wavelet analysis, SETARMA and GARCH models. In the next chapter, we evaluate the accuracy and performance of the proposed forecasting approaches and accordingly compare each one to another as well as to the baseline ARIMA models.

Chapter 8

Experimental Evaluation

In this chapter we evaluate accuracy and performance aspects of the proposed forecasting approaches and compare them to those of the baseline ARIMA models. In general, we achieve this evaluation as follows. First, we apply the proposed forecasting approaches and the baseline ARIMA models to the collected QoS datasets, which are discussed in Chapter 4. We then compute and investigate relative predictive errors and the MAPE metric as a measure for the accuracy of forecasting QoS values, contingency table-based metrics as a measure for the accuracy of forecasting QoS violations, and time required to construct and use the time series model as a measure for the performance.

In the rest of this chapter, we first introduce the experiment setup. We then investigate and discuss in detail the results. Finally, we present general discussion based on the results and highlight threats to validity of the work.

8.1 Experiment Setup

As mentioned in Chapter 3, the accuracy and performance aspects of the proposed forecasting approaches need to be evaluated. In particular, the accuracy of the proposed forecasting approaches is classified into two types; the accuracy of forecasting QoS values and the accuracy of forecasting QoS violations. In addition, the perfor-

mance is measured by the time required by the forecasting approaches to construct and use the time series model. Accordingly, we identify the following main evaluation questions.

EQ1: Are the proposed forecasting approaches able to capture the dynamic behavior of QoS attributes and improve the forecasting accuracy compared to the baseline ARIMA model?

EQ2: To what extent the proposed forecasting approaches are able to correctly forecast QoS violations compared to the baseline ARIMA model?

EQ3: What time is required for the forecasting approaches to automatically construct and use the forecasting model?

In order to answer **EQ1**, the proposed forecasting approaches and baseline ARIMA models are applied to the real-world response time and time between failures datasets that we have collected as discussed in detail in Chapter 4. Specifically, the datasets are classified according to the main characteristics of the QoS attributes into three groups which are:

- Nonlinearly dependent with constant variance over time.
- Linearly dependent with volatility clustering.
- Nonlinearly dependent with volatility clustering.

Where each group includes 100 datasets of response time and 40 datasets of time between failures. In order to construct the forecasting model, in the case of response time the forecasting approaches and the ARIMA model use the first 500 observations in the dataset as a training set. However, in the case of time between failures the number of observations considered as a training set depends on the size of the dataset, especially most of the size of time between failures datasets is less than 200 observations. The constructed forecasting models by the forecasting approaches and the ARIMA model are used to compute the predictions, and for each dataset prediction the relative prediction errors are computed as follows:

$$error_t = |\frac{y_t - \hat{y}_t}{y_t}| \times 100, \quad for\ t = 1, 2, \ldots, n \tag{8.1}$$

where y_t and $\hat{y}_t$ are the real and predicted values, respectively. These errors are analyzed using boxplots and descriptive statistics. In addition, the MAPE metric (in Equation 3.7), which is discussed in Chapter 3, is computed. The non-parametric Mann-Whitney test [77] is used to test whether the proposed forecasting approaches significantly outperform the baseline ARIMA model in terms of forecasting accuracy. To quantify the difference in MAPE values, the effect size [51] is computed as follows:

$$effect\ size = \frac{MAPE_{ARIMA} - MAPE_{Proposed}}{\sqrt{(\sigma^2_{ARIMA} + \sigma^2_{Proposed})/2}} \tag{8.2}$$

where MAPE_{ARIMA} and σ^2_{ARIMA} refer to the MAPE value and the variance of relative prediction errors produced by the baseline ARIMA models, respectively, and $\text{MAPE}_{Proposed}$ and $\sigma^2_{Proposed}$ refer to the MAPE value and the variance of relative prediction errors produced by one of the proposed forecasting approaches, respectively. Moreover, the relative forecasting accuracy improvement (RAI) is measured using a metric which is defined as follows:

$$RAI = \frac{MAPE_{ARIMA} - MAPE_{Proposed}}{MAPE_{ARIMA}} \times 100 \tag{8.3}$$

In order to address **EQ2**, requirements of the response time and time between failures of each Web service are specified, and then the proposed forecasting approaches and the baseline ARIMA model are applied (using the same setting in **EQ1**) to forecast the violations of these requirements. After that, contingency table-based metrics, especially negative predictive value (NPV), specificity value (SV), F-measure value (FMV), and accuracy value (AV) metrics discussed in Chapter 3, are computed for each Web service in order to assess the forecasting accuracy of requirement violations considering different cases. In addition, the Mann-Whitney test is used to test whether the proposed forecasting approaches significantly outperform the baseline ARIMA model in terms of these contingency table-based metrics, along with computing the effect size values.

EQ3 is simply addressed by computing the time required for the forecasting

approaches and the baseline ARIMA models to automatically construct and use the forecasting model. As a platform for our experiments, we used a Windows-based PC equipped with a 3.00 GHz dual-core processor and 4GB main memory.

8.2 Results

In this section, the experiments results are introduced and discussed for each evaluation question, and separately for the response time and time between failures.

8.2.1 EQ1. Improving Forecasting Accuracy of QoS Values Compared to Baseline ARIMA Model

8.2.1.1 Nonlinearly Dependent QoS Attributes

The boxplots of the relative prediction errors produced by the proposed forecasting approach I and the baseline ARIMA model for nonlinearly dependent response time and time between failures are depicted in Figures 8.1 and 8.2, respectively. In addition, the MAPE values of the forecasting approach I and the baseline ARIMA model are reported separately for each dataset in Table 8.1. (It is worth mentioning that the detailed description of the Web services labeled in the Tables is introduced in Appendix A.)

The boxplots in Figures 8.1 and 8.2 indicate that the forecasting approach I can provide more accurate forecasts than the ARIMA model, where the prediction errors exhibited by this approach are significantly lower than those of ARIMA models. This result is confirmed by the Mann-Whitney test where the p-values < 0.05. More precisely, the forecasting approach I produces MAPE values are on average 4.75 and 18.99 compared to 6.08 and 24.85 produced by the ARIMA model with effect size values are 0.26 and 0.35 for the response time and time between failures, respectively. This highlights that the forecasting approach I achieves forecasting accuracy improvement of about 21.4% in the case of the response time and bout 23% in the case of the time between failures. It is worth initially noting that the

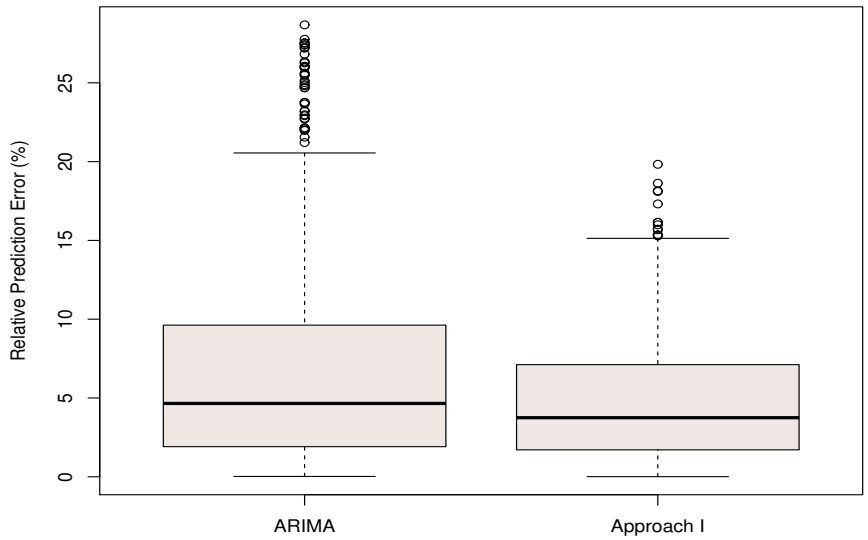


Figure 8.1: Boxplots of relative prediction errors for nonlinearly dependent response time

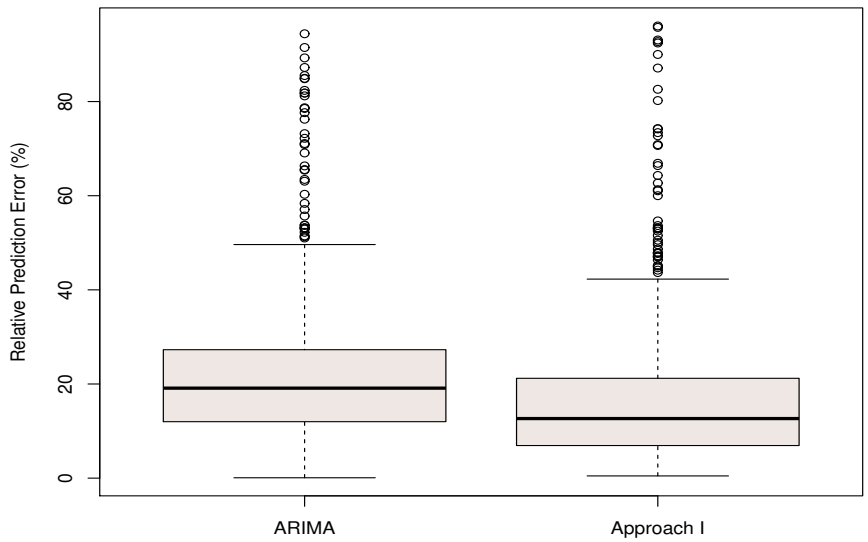


Figure 8.2: Boxplots of relative prediction errors for nonlinearly dependent time between failures

accuracy of the forecasting approach I and the baseline ARIMA model in the case of the response time is better than that in the case of the time between failures. This point will be discussed in detail at the end of this chapter.

These boxplots show another observation that the variation of prediction errors exhibited by the proposed forecasting approach I is significantly lower than that of the ARIMA model. Where, in the case of the response time 50% of the prediction errors are within (1.71, 7.11) with an interquartile range (IQR) = 5.4 for the forecasting approach I, and within (1.91, 9.61) with an IQR = 7.1 for the ARIMA model. Similarly, in the case of the time between failures 50% of the prediction errors are within (12.66, 21.21) with an IQR = 14.3 for the forecasting approach I, and within (19.12, 27.28) with an IQR = 15.3 for the ARIMA model. This indicates that the forecasting accuracy of the approach I is more stable across different QoS datasets than that of the ARIMA model.

For each Web service in Table 8.1, the results show that the forecasting approach I outperforms the ARIMA model in all the cases of the response time and time between failures. This result is confirmed by the Mann-Whitney test where the p-values $<$ 0.05. The lowest and highest accuracy improvement of the forecasting approach I compared to the ARIMA model for the response time are in the cases of WS_1 with the RAI is about 11.7% and WS_2 with the RAI is about 30.3% respectively, and for the time between failures are in the cases of WS_{14} with the RAI is about 15.8% and WS_{13} with the RAI is about 31% respectively.

- *The forecasting approach I outperforms the ARIMA model in forecasting QoS values with accuracy improvement of about 21.4% and 23% for the response time and time between failures, respectively.*

WS_{id}	ARIMA	Approach I	
	MAPE	MAPE	RAI
WS_1	7.18	6.34	11.72
WS_2	8.34	5.81	30.32
WS_3	5.41	4.33	19.86
WS_4	3.55	3.13	11.99
WS_5	4.92	3.68	25.26
WS_6	5.37	3.86	28.07
WS_7	5.54	4.88	11.91
WS_8	6.64	4.90	26.30
WS_9	11.52	8.79	23.67
WS_{10}	2.34	1.76	24.80
Average	6.08	4.75	21.39

(a) Results for response time

WS_{id}	ARIMA	Approach I	
	MAPE	MAPE	RAI
WS_2	25.74	19.86	22.84
WS_5	27.91	21.20	24.04
WS_{11}	26.29	19.65	25.25
WS_{12}	17.40	13.83	20.50
WS_{13}	30.55	21.09	30.98
WS_{14}	18.54	15.61	15.79
WS_{15}	29.38	21.22	27.76
WS_{16}	14.53	11.38	21.64
WS_{17}	29.21	22.66	22.42
WS_{18}	28.93	23.39	19.15
Average	24.85	18.99	23.04

(b) Results for time between failures

Table 8.1: MAPE and RAI values for nonlinearly dependent QoS attributes

8.2.1.2 Linearly Dependent QoS Attributes with Volatility Clustering

The boxplots of the relative prediction errors produced by the proposed forecasting approaches II and III and the baseline ARIMA model for linearly dependent response time and time between failures with volatility clustering are depicted in Figures 8.3 and 8.4, respectively. Additionally, the MAPE values of the forecasting approaches II and III and the baseline ARIMA model are reported separately for each dataset in Table 8.2.

The boxplots in Figures 8.3 and 8.4 highlight that the forecasting approaches II and III can provide more accurate forecasts than the ARIMA model, where the prediction errors exhibited by these approaches are significantly lower than those of ARIMA models. This result is confirmed by the Mann-Whitney test where the p-values < 0.05. In fact, the MAPE values are 5.30 and 24.60 produced by the ARIMA model compared to 4.28 and 19.08 produced by the forecasting approach II with effect size values are 0.24 and 0.32, and compared to 2.94 and 14.85 produced by the forecasting approach III with effect size values are 0.63 and 0.56 for the response

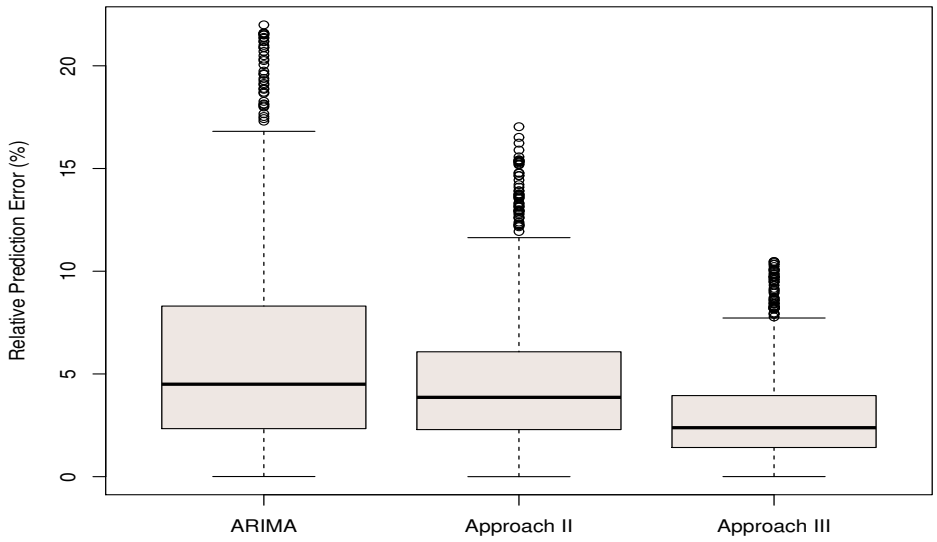


Figure 8.3: Boxplots of relative prediction errors for linearly dependent response time with volatility clustering

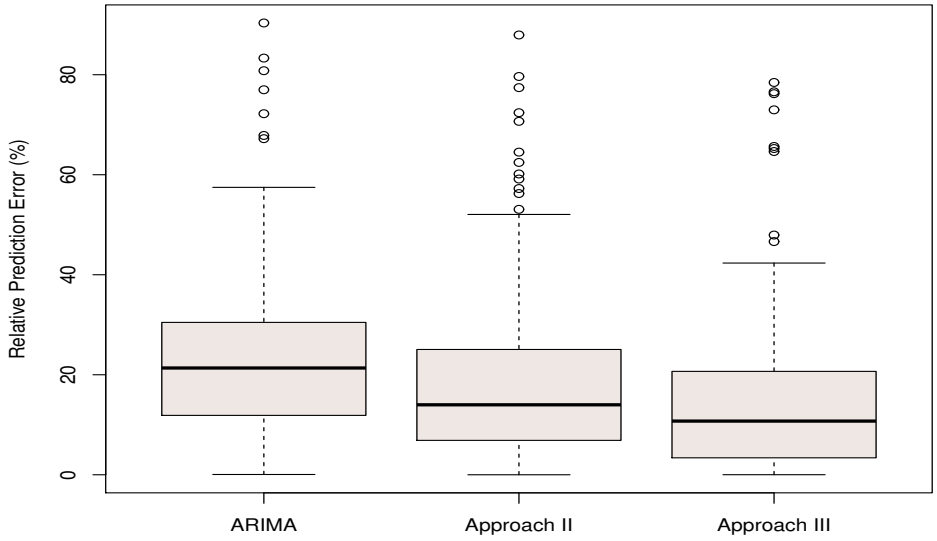


Figure 8.4: Boxplots of relative prediction errors for linearly dependent time between failures with volatility clustering

time and time between failures, respectively. This highlights that the forecasting approaches II and III achieve forecasting accuracy improvement of about 20.3% and 40.5%, respectively, in the case of the response time and bout 19.5% and 39.8%, respectively, in the case of the time between failures. It is worth noting that the forecasting approach III achieves accuracy improvement is about double times of that achieved by the forecasting approach II in both cases of the response time and time between failures.

These boxplots show that the variations of prediction errors exhibited by the proposed forecasting approaches II and III are significantly lower than those of the ARIMA model. In the case of the response time, 50% of the prediction errors are within (2.29, 6.08) with an IQR = 3.8 for the forecasting approach II, within (1.42, 3.95) with an IQR = 2.5 for the forecasting approach III, and within (2.34, 8.30) with an IQR = 6.0 for the ARIMA model. Similarly, in the case of the time between failures 50% of the prediction errors are within (6.89, 24.78) with an IQR = 17.9 for the forecasting approach II, within (3.40, 20.54) with an IQR = 17.1 for the forecasting approach III, and within (11.88, 30.47) with an IQR = 18.6 for the ARIMA model. This indicates that the forecasting accuracy of the approaches II and III is more stable across different QoS datasets than that of the ARIMA model. In particular, this result is more highlighted in the case of the response time than in the case of the time between failures, and for the forecasting approach III than for the forecasting approach II.

The results in Table 8.2 show that the forecasting approaches II and III outperform the ARIMA model in all the cases of the response time and time between failures, and the Mann-Whitney test confirms this result where the p-values < 0.05. The lowest and highest accuracy improvement of the forecasting approach II compared to the ARIMA model for the response time are in the cases of WS_{26} with the RAI is about 10.2% and WS_{18} with the RAI is about 36.8% respectively, and for the time between failures are in the cases of WS_{28} with the RAI is about 9.2% and WS_{20} with the RAI is about 46% respectively. Similarly, the lowest and highest accuracy

	ARIMA	Approach II		Approach III	
WS_{id}	MAPE	MAPE	RAI	MAPE	RAI
WS_{18}	3.57	2.25	36.81	2.70	24.32
WS_{19}	3.07	2.28	25.77	1.92	37.36
WS_{20}	7.73	6.10	21.14	3.76	51.34
WS_{21}	6.88	5.90	14.27	3.84	44.26
WS_{22}	7.92	6.13	22.58	3.88	50.97
WS_{23}	10.17	8.59	15.55	4.41	56.60
WS_{24}	3.05	2.73	10.57	2.28	25.51
WS_{25}	2.40	1.62	32.81	1.39	42.01
WS_{26}	4.11	3.69	10.19	2.44	40.54
WS_{27}	4.11	3.55	13.54	2.78	32.30
Average	5.30	4.28	20.32	2.94	40.52

(a) Results for response time

	ARIMA	Approach II		Approach III	
WS_{id}	MAPE	MAPE	RAI	MAPE	RAI
WS_{1}	26.25	16.61	10.57	14.96	43.00
WS_{8}	20.88	14.69	32.81	12.36	40.78
WS_{9}	36.27	32.03	11.70	20.02	44.81
WS_{20}	12.35	6.67	46.02	7.28	41.06
WS_{28}	25.16	22.83	9.24	15.57	38.09
WS_{29}	41.15	35.10	14.27	26.04	36.71
WS_{30}	22.10	15.17	31.35	14.14	36.04
WS_{31}	13.94	7.81	15.55	7.83	43.83
WS_{32}	25.35	22.27	10.19	15.94	37.12
WS_{33}	22.51	17.65	13.54	14.31	36.45
Average	24.60	19.08	19.52	14.85	39.79

(b) Results for time between failures

Table 8.2: MAPE and RAI values for linearly dependent QoS attributes with volatility clustering

improvement of the forecasting approach III compared to the ARIMA model for the response time are in the cases of WS_{18} with the RAI is about 24.3% and WS_{23} with the RAI is about 56.6% respectively, and for the time between failures are in the cases of WS_{30} with the RAI is about 36% and WS_{9} with the RAI is about 44.8% respectively.

- ► *The forecasting approaches II and III outperform the ARIMA model in forecasting QoS values with accuracy improvement of about 20.3% and 40.5%, respectively in the case of the response time, and of about 19.5% and 39.8%, respectively in the case of the time between failures.*
- ► *The forecasting approach III achieves accuracy improvement is about double times of that achieved by the forecasting approach II.*

8.2.1.3 Nonlinearly Dependent QoS Attributes with Volatility Clustering

The boxplots of the relative prediction errors produced by the five proposed forecasting approaches and the baseline ARIMA model for nonlinearly dependent response time and time between failures with volatility clustering are depicted in Figures 8.5 and 8.6, respectively. Moreover, the MAPE values are reported separately for each dataset in Table 8.4.

The results in Figures 8.5 and 8.6 highlight the following main points:

- First, each one of the five proposed forecasting approaches can provide more accurate forecasts than the ARIMA model, as the prediction errors exhibited by these approaches are significantly lower than those of ARIMA models. This result is confirmed by the Mann-Whitney test where the p-values < 0.05. More precisely, in the case of the response time, the MAPE values are 13.45 produced by the ARIMA model compared to 11.11, 11.53, 9.58, 10.00, and 6.48 produced by the forecasting approaches I, II, III, IV, and V respectively with effect size values are 0.21, 0.17, 0.36, 0.32, and 0.74 respectively. On the other hand, in the case of the time between failures, the MAPE values are 26.98 produced by the ARIMA model compared to 21.66, 22.84, 18.31, 18.56, and 15.11 produced by the forecasting approaches I, II, III, IV, and V respectively with effect size values are 0.35, 0.28, 0.60, 0.58, and 0.87 respectively. This highlights that the five forecasting approaches I, II, III, IV, and V achieve forecasting accuracy improvement of about 19.5%, 15.6%, 28.3%, 27.4%, and 50.4%, respectively, in the case of the response time and bout 19.4%, 15.7%, 31.3%, 31.6%, and 43.3%, respectively, in the case of the time between failures.

- Second, the variation of prediction errors exhibited by each one of the proposed forecasting approaches is significantly lower than that of the ARIMA model. This result is more highlighted in Table 8.3 by reporting the first and third quartiles (Q1 and Q3) and the interquartile range (IQR) values of the

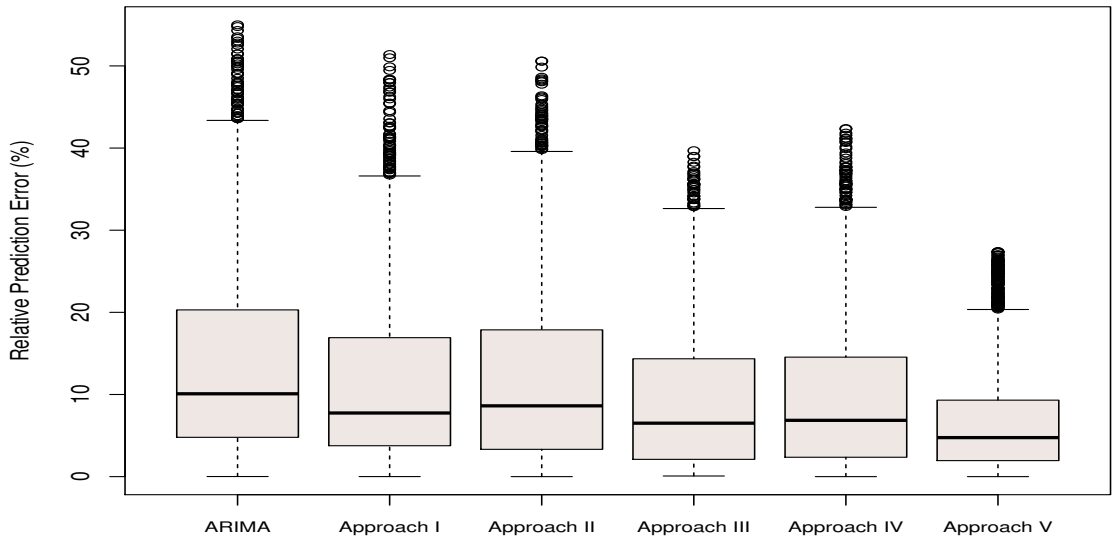


Figure 8.5: Boxplots of relative prediction errors for nonlinearly dependent response time with volatility clustering

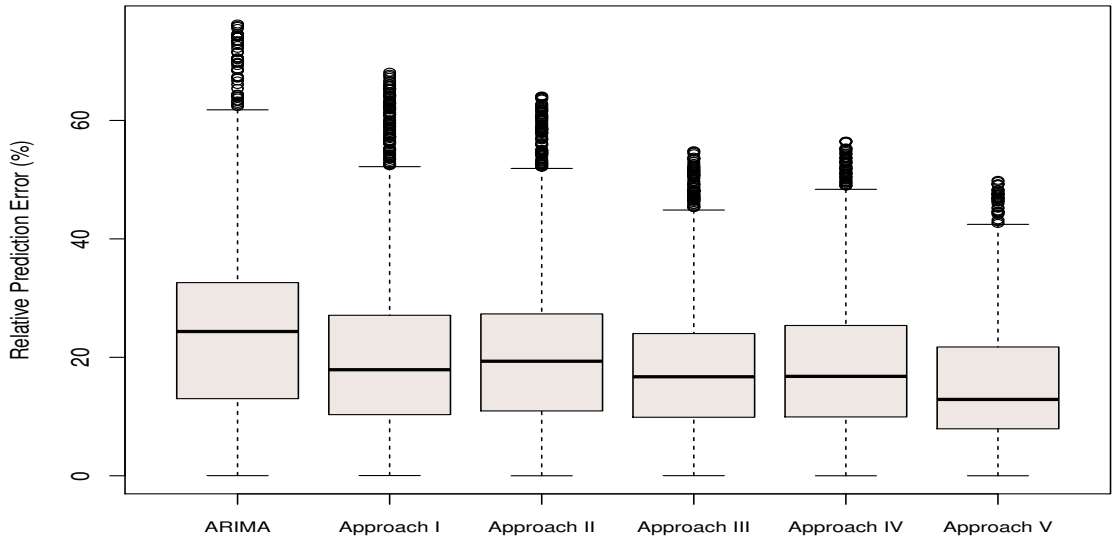


Figure 8.6: Boxplots of relative prediction errors for nonlinearly dependent time between failures with volatility clustering

prediction errors for both cases of the response time and time between failures. Moreover, it is evident from this Table that the forecasting approach V has the lowest variation of prediction errors.

- Third, the forecasting approaches I and II have almost equivalent forecasting accuracy, and similarly for the forecasting approaches III and IV. However, the former two approaches have less accuracy than that of the latter ones. Moreover, the forecasting approach V achieves the best forecasting accuracy.

For each Web service in Table 8.4, the results show that each one of the five forecasting approaches outperforms the ARIMA model in all the cases of the response time and time between failures. This result is confirmed by the Mann-Whitney test where the p-values < 0.05. The lowest and highest accuracy improvement of the five forecasting approaches compared to the ARIMA model for the response time are in the cases of WS_{39} with the RAI is about 7.0% and WS_{30} with the RAI is about 56.9% respectively, and for the time between failures are in the cases of WS_3 with the RAI is about 5.3% and WS_{44} with the RAI is about 50.4% respectively.

- ► *The five proposed forecasting approaches outperform the ARIMA model in forecasting QoS values with accuracy improvement of about 15.6% to 50.4% in both cases of the response time and time between failures.*
- ► *The forecasting approaches I and II have almost equivalent forecasting accuracy, and similarly for the forecasting approaches III and IV.*
- ► *The forecasting approach V achieves the best forecasting accuracy.*

	Response Time			Time Between Failures		
	Q1	Q3	IQR	Q1	Q3	IQR
ARIMA	4.79	20.30	15.51	13.04	32.61	19.57
Approach I	3.76	16.92	13.16	10.32	27.10	16.78
Approach II	3.33	17.87	14.54	10.96	27.32	16.36
Approach III	2.10	14.35	12.25	9.88	23.99	14.11
Approach IV	2.36	14.54	12.18	9.94	25.38	15.44
Approach V	1.95	9.31	7.36	7.93	21.74	13.81

Table 8.3: Quartiles (Q1 and Q3) and interquartile range (IQR) for MAPE values for nonlinearly dependent QoS attributes with volatility clustering

	ARIMA	Approach I		Approach II		Approach III		Approach IV		Approach V	
WS_{id}	MAPE	MAPE	RAI	MAPE	RAI	MAPE	RAI	MAPE	RAI	MAPE	RAI
WS_{30}	22.39	19.61	12.40	19.89	11.16	14.49	35.28	17.61	21.34	9.64	56.94
WS_{34}	6.22	4.26	31.56	5.47	12.04	4.50	27.57	4.98	19.99	3.01	51.63
WS_{35}	18.32	14.77	19.37	15.51	15.32	12.92	29.45	13.39	26.87	8.28	54.77
WS_{36}	19.43	16.19	16.65	15.70	19.16	17.16	11.66	15.08	22.38	10.59	45.46
WS_{37}	11.81	8.73	26.13	9.45	19.98	8.55	27.64	7.18	39.23	5.52	53.25
WS_{38}	8.69	5.56	36.07	6.85	21.18	5.96	31.39	5.66	34.89	4.62	46.84
WS_{39}	16.89	15.20	10.00	15.71	6.99	11.26	33.31	13.33	21.07	8.00	52.62
WS_{40}	19.59	17.50	10.66	17.61	10.08	12.85	34.38	15.26	22.08	8.98	54.16
WS_{41}	4.19	3.54	15.44	3.07	26.77	3.32	20.72	2.63	37.19	2.39	42.86
WS_{42}	6.97	5.79	16.95	6.03	13.60	4.81	31.10	4.92	29.41	3.78	45.75
Average	13.45	11.11	19.52	11.53	15.63	9.58	28.25	10.00	27.44	6.48	50.43

(a) Results for response time

	ARIMA	Approach I		Approach II		Approach III		Approach IV		Approach V	
WS_{id}	MAPE	MAPE	RAI	MAPE	RAI	MAPE	RAI	MAPE	RAI	MAPE	RAI
WS_{3}	24.42	21.82	10.66	23.11	5.34	19.59	19.78	13.96	42.84	13.49	44.76
WS_{6}	26.34	22.91	13.02	23.55	10.62	16.20	38.50	16.41	37.69	14.79	43.87
WS_{7}	25.52	22.30	12.60	22.67	11.16	18.04	29.31	17.91	29.80	15.76	38.22
WS_{22}	20.57	16.09	21.76	15.02	26.96	14.06	31.64	13.51	34.31	11.81	42.58
WS_{23}	18.38	14.51	21.03	13.68	25.53	14.02	23.70	13.82	24.79	12.61	31.37
WS_{38}	30.68	21.96	28.41	26.33	14.17	21.69	29.31	22.19	27.67	17.15	44.10
WS_{40}	32.99	21.22	35.69	27.69	16.09	20.81	36.92	24.57	25.54	16.90	48.79
WS_{43}	26.80	21.39	20.21	23.67	11.69	19.53	27.13	15.25	43.11	14.79	44.82
WS_{44}	32.84	26.58	19.09	26.62	18.95	16.70	49.16	22.15	32.55	16.29	50.40
WS_{45}	31.23	27.79	11.03	26.08	16.50	22.49	27.97	25.84	17.26	17.55	43.81
Average	26.98	21.66	19.35	22.84	15.70	18.31	31.34	18.56	31.56	15.11	43.27

(b) Results for time between failures

Table 8.4: MAPE and RAI values for nonlinearly dependent QoS attributes with volatility clustering

8.2.2 EQ2. Improving Forecasting Accuracy of QoS Violations Compared to Baseline ARIMA Models

8.2.2.1 Nonlinearly Dependent QoS Attributes

The boxplots of the contingency table-based metrics produced by the proposed forecasting approach I and the baseline ARIMA model for nonlinearly dependent response time and time between failures are depicted in Figures 8.7 and 8.8 respectively, while the average values of these metrics are reported in Table 8.5. Generally, the results show that both the forecasting approach I and the baseline ARIMA model provide high values for the negative predictive value (NPV), specificity value (SV), and accuracy value (AV) metrics. However, the F-measure value (FMV) is relatively very low. This observation is highlighted in both cases of the response time and time between failures, and this result is expected as discussed in Chapter 3 (in Section 3.3).

The results highlight that the forecasting approach I achieves small improvement in the negative predictive value over the ARIMA model, since the values are almost the same, about 95.7%, in the case of the response time and increased from 85.8% to 86.3% with effect size value is 0.13 in the case of the time between failures. The Mann-Whitney test reports that this improvement is insignificant where the p-values > 0.05.

Regarding the specificity metric, the forecasting approach I slightly improves this metric in the case of response time, since it is increased from 97.9% to 98.5% with effect size value is 0.11. However, this improvement is relatively high in the case of time between failures, as the value is 85.3% produced by the ARIMA model compared to 99.3% produced by the forecasting approach I, with effect size value is 0.41. Moreover, the Mann-Whitney test confirms this result with p-values < 0.05.

The results show that the F-measure values produced by the forecasting approach I are on average 33.09% and 31.68% compared to 20.46% and 22.91% produced by the ARIMA model with effect size values are 0.65 and 0.52 in the cases of response

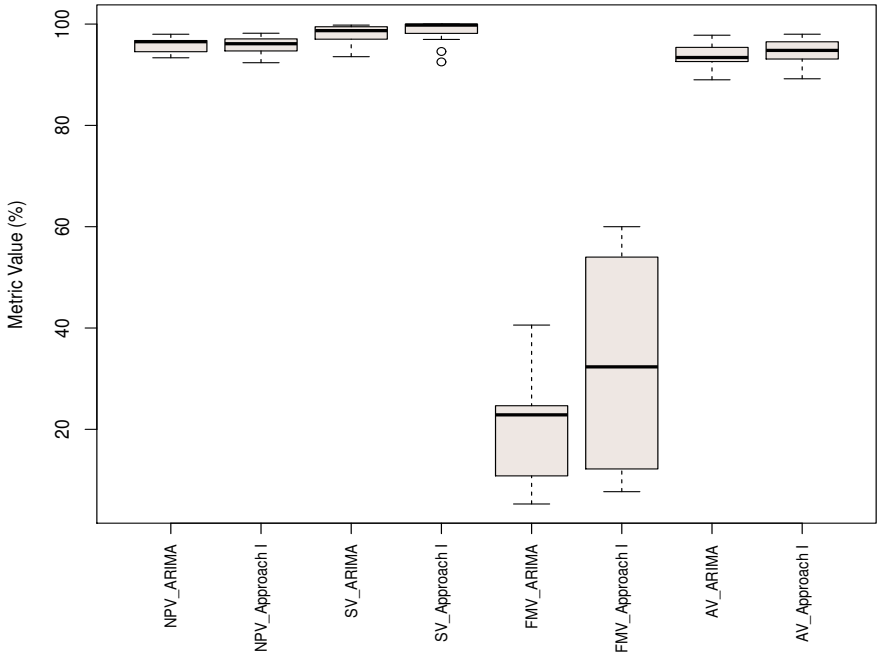


Figure 8.7: Boxplots of contingency table-based metrics for nonlinearly dependent response time

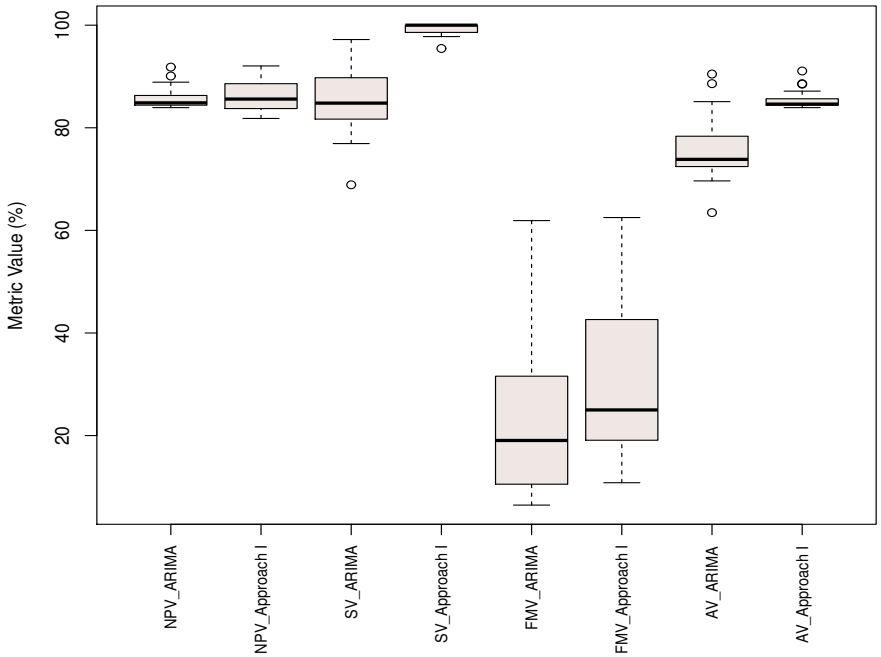


Figure 8.8: Boxplots of contingency table-based metrics for nonlinearly dependent time between failures

	Response Time				Time Between Failures			
	NPV	SV	FMV	AV	NPV	SV	FMV	AV
ARIMA	95.71	97.92	20.46	93.37	85.81	85.31	22.91	75.87
Approach I	95.72	98.46	33.09	94.79	86.28	99.29	31.68	85.39

Table 8.5: Average of contingency table-based metrics for nonlinearly dependent QoS attributes

time and time between failures, respectively. This result implies that most of the accuracy gains achieved by the forecasting approach I is in the case of the F-measure value with relative improvement is about 61.7% and 47.0% for response time and time between failures, respectively. The Mann-Whitney test confirms this result where the p-values < 0.05. This indicates that the forecasting approach I improves the precision and recall values.

Finally, the results highlight that the accuracy metric is slightly improved in the case of response time, where the value is increased from 93.4% produced by the ARIMA model to 94.8% produced by the forecasting approach I, with effect size value is 0.12. However, the Mann-Whitney test reports that this improvement is insignificant where the p-value > 0.05. On the other hand, the accuracy metric is relatively highly improved in the case of time between failures, where the value is 75.9% produced by the ARIMA model compared to 85.4% produced by the forecasting approach I, with effect size value is 0.38. The Mann-Whitney test confirms this result where the p-value < 0.05.

- ▶ *The forecasting approach I and ARIMA model provide high values for the negative predictive value, specificity, and accuracy metrics, however, the F-measure value is relatively very low.*
- ▶ *Compared to the ARIMA model, the forecasting approach I achieves insignificant relative improvement for the negative predictive value, specificity, and accuracy in the case of response time, however, significant relative improvement for the specificity and accuracy in the case of time between failures.*

► *The forecasting approach I achieves the highest relative improvement, which is about 61.7% and 47.0%, for the F-measure value in the cases of response time and time between failures, respectively.*

8.2.2.2 Linearly Dependent QoS Attributes with Volatility Clustering

The boxplots of the contingency table-based metrics produced by the proposed forecasting approaches II and III and the baseline ARIMA model for linearly dependent response time and time between failures with volatility clustering are depicted in Figures 8.9 and 8.10 respectively, while the average values of these metrics are reported in Table 8.6. As expected, the results show that generally the values of the negative predictive value, specificity, and accuracy metrics are higher than those of the F-measure value metric.

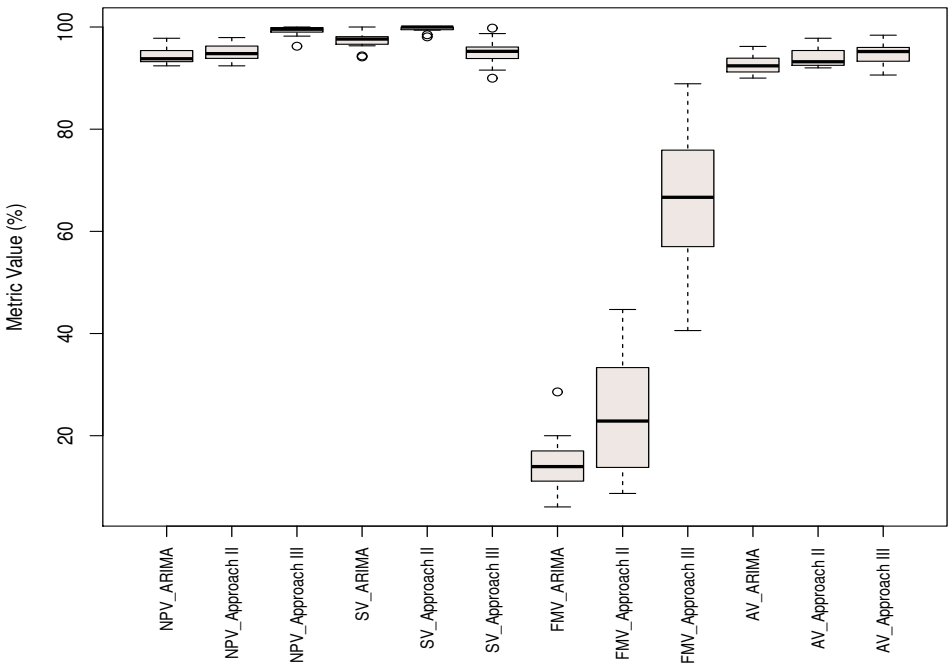


Figure 8.9: Boxplots of contingency table-based metrics for linearly dependent response time with volatility clustering

As a comparison between the forecasting approach II and the baseline ARIMA

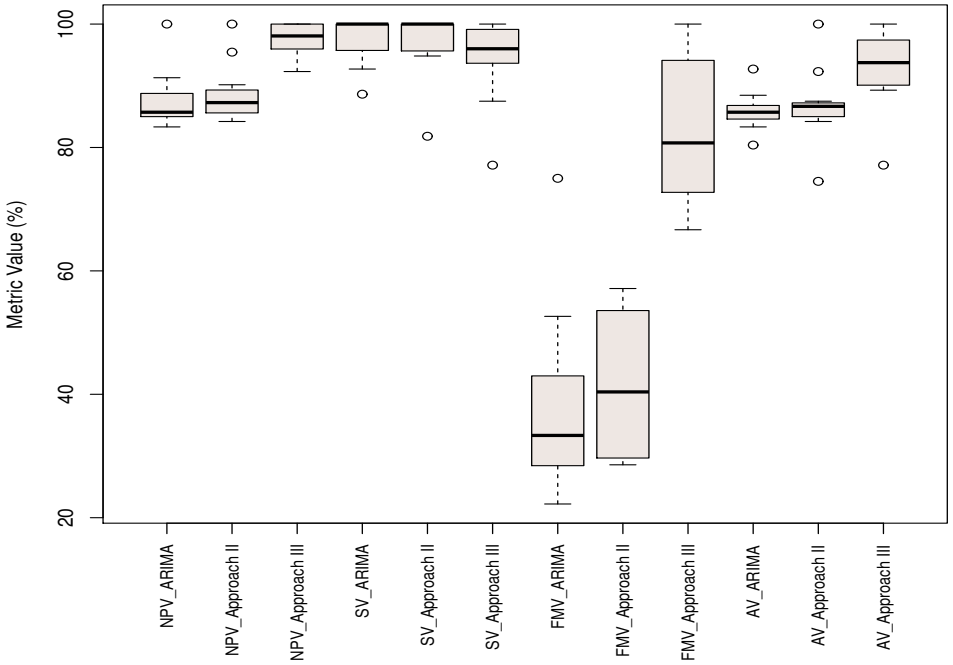


Figure 8.10: Boxplots of contingency table-based metrics for linearly dependent time between failures with volatility clustering

	Response Time				Time Between Failures			
	NPV	SV	FMV	AV	NPV	SV	FMV	AV
ARIMA	94.40	97.24	14.38	92.71	87.67	97.53	36.05	85.83
Approach II	95.10	99.57	23.83	94.05	88.71	97.68	41.62	86.78
Approach III	99.19	95.09	64.89	94.82	97.46	94.56	82.48	92.88

Table 8.6: Average of contingency table-based metrics for linearly dependent QoS attributes with volatility clustering

model, the results in Table 8.6 and the boxplots indicate that the forecasting approach II achieves small relative improvement in the negative predictive value, specificity, and accuracy metrics, however, it achieves high relative improvement in the F-measure value metric. More precisely, the values of the negative predictive value are increased from 94.4% and 87.7% produced by the ARIMA model to 95.1% and 88.7% produced by the forecasting approach II, with effect size values are 0.08 and 0.15 in the cases of response time and time between failures, respectively. The

Mann-Whitney test reports that the improvement is insignificant where the p-values > 0.05. The values of specificity are increased from 97.2% and 97.5% produced by the ARIMA model to 99.6% and 97.7% produced by the forecasting approach II, with effect size values are 0.25 and 0.13 in the cases of response time and time between failures, respectively. The Mann-Whitney test reports that this improvement is significant in the case of response time (p-value < 0.05) and, however, is insignificant in the case of time between failures (p-value > 0.05). Similarly, the values of accuracy metric are increased from 92.7% to 94.1% with effect size value is 0.10, and from 85.8% to 86.8% with effect size value is 0.16, in the cases of response time and time between failures, respectively. The Mann-Whitney test reports that this improvement is insignificant in the cases of response time and time between failures where the p-values > 0.05. Finally, the results show that the highest accuracy improvement achieved by the forecasting approach II is in the case of F-measure value metric, where its values are increased from 14.38% and 36.05% to 23.83% and 41.62%, with effect size values are 0.61 and 0.34 in the cases of response time and time between failures, respectively. This implies that the relative improvement achieved by the forecasting approach II for the F-measure value metric is about 65.7% and 15.5% in the cases of response time and time between failures, respectively. The Mann-Whitney test confirms this result where the p-value < 0.05.

Regarding the forecasting approach III compared to the baseline ARIMA model, the results in Figures 8.9 and 8.10 and Table 8.6 highlight that the forecasting approach III highly improves the negative predictive value, F-measure value, and accuracy metrics, however, it loses some accuracy in the specificity metric. More precisely, the negative predictive values are increased from 94.4% and 87.7% to 99.2% and 97.5% with effect size values are 0.29 and 0.31, the F-measure values are increased from 14.4% and 36.1% to 64.9% and 82.5% with effect size values are 1.6 and 1.2, and the accuracy values are increased from 92.7% and 85.8% to 94.8% and 92.9% with effect size values are 0.17 and 0.29 in the cases of response time and time between failures, respectively. However, the specificity values are

decreased from 97.2% and 97.5% to 95.1% and 94.6% with effect size values are 0.19 and 0.21 in the cases of response time and time between failures, respectively. The Mann-Whitney test confirms the significance of these results where all the p-values < 0.05.

- *The forecasting approaches II and III and ARIMA model provide high values for the negative predictive value, specificity, and accuracy, and relatively low values for the F-measure value.*
- *Compared to the ARIMA model, the forecasting approach II slightly improves the negative predictive value, specificity, and accuracy, and highly improves the F-measure value.*
- *Compared to the ARIMA model, the forecasting approach III highly improves the negative predictive value, F-measure value, and accuracy, however, it loses some accuracy in the specificity metric.*
- *The forecasting approaches II and III are not equivalent in terms of contingency table-based metrics.*

8.2.2.3 Nonlinearly Dependent QoS Attributes with Volatility Clustering

The boxplots of the contingency table-based metrics produced by the five proposed forecasting approaches and the baseline ARIMA model for nonlinearly dependent response time and time between failures with volatility clustering are depicted in Figures 8.11 and 8.12 respectively, while the average values of these metrics are reported in Table 8.7.

The results in Figures 8.11 and 8.12 and Table 8.7 highlight the following main points:

- First, the five proposed forecasting approaches and ARIMA model provide values of the negative predictive value, specificity, and accuracy metrics that

are higher than those of the F-measure value in both cases of response time and time between failures. This observation is similarly highlighted in previous two subsections.

- Second, the forecasting approaches I, II, and IV achieve small improvement in the negative predictive value, specificity, and accuracy metrics compared to the baseline ARIMA model in both cases of response time and time between failures. The Mann-Whitney test reports that the improvement in the specificity is almost significant and, however, is almost insignificant in the other two metrics, except in the accuracy metric for the forecasting approach IV. Additionally, the most accuracy improvement achieved by these three forecasting approaches is in the F-measure value metric, with the Mann-Whitney p-values < 0.05. In particular, the highest improvement in the F-measure value metric is achieved by the forecasting approach IV, where its values are increased from 10.29% and 12.30% to 23.93% and 22.34% with effect size values are 0.73 and 0.59 in the cases of response time and time between failures, respectively.

- Third, compared to the baseline ARIMA model, the forecasting approaches III and V highly improve the negative predictive value, F-measure value, and accuracy metrics, however, they lose some accuracy in the specificity metric. In particular for the forecasting approach V, the negative predictive values are increased from 93.5% and 84.3% to 99.5% and 96.3% with effect size values are 0.54 and 0.69, the F-measure values are increased from 10.3% and 12.3% to 75.0% and 82.1% with effect size values are 1.96 and 2.13, and the accuracy values are increased from 92.0% and 82.2% to 95.4% and 92.6% with effect size values are 0.38 and 0.59 in the cases of response time and time between failures, respectively. However, the specificity values are decreased from 97.9% and 96.3% to 95.6% and 92.5% with effect size values are 0.17 and 0.21 in the cases of response time and time between failures, respectively. The Mann-Whitney test confirms the significance of these results where all the p-values < 0.05.

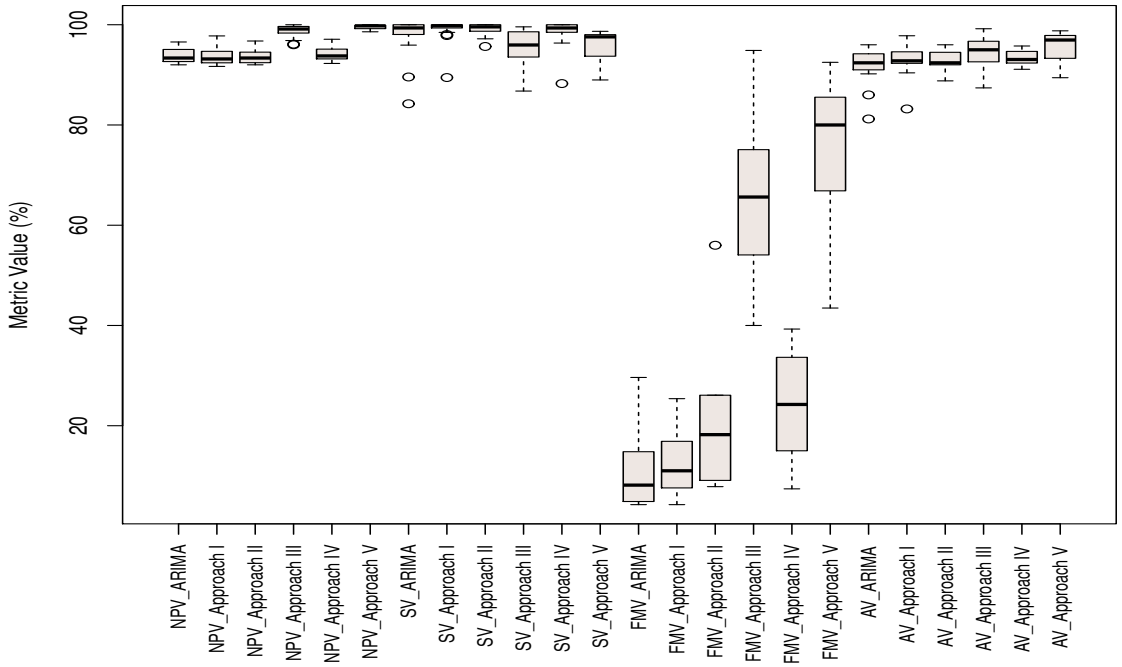


Figure 8.11: Boxplots of contingency table-based metrics for nonlinearly dependent response time with volatility clustering

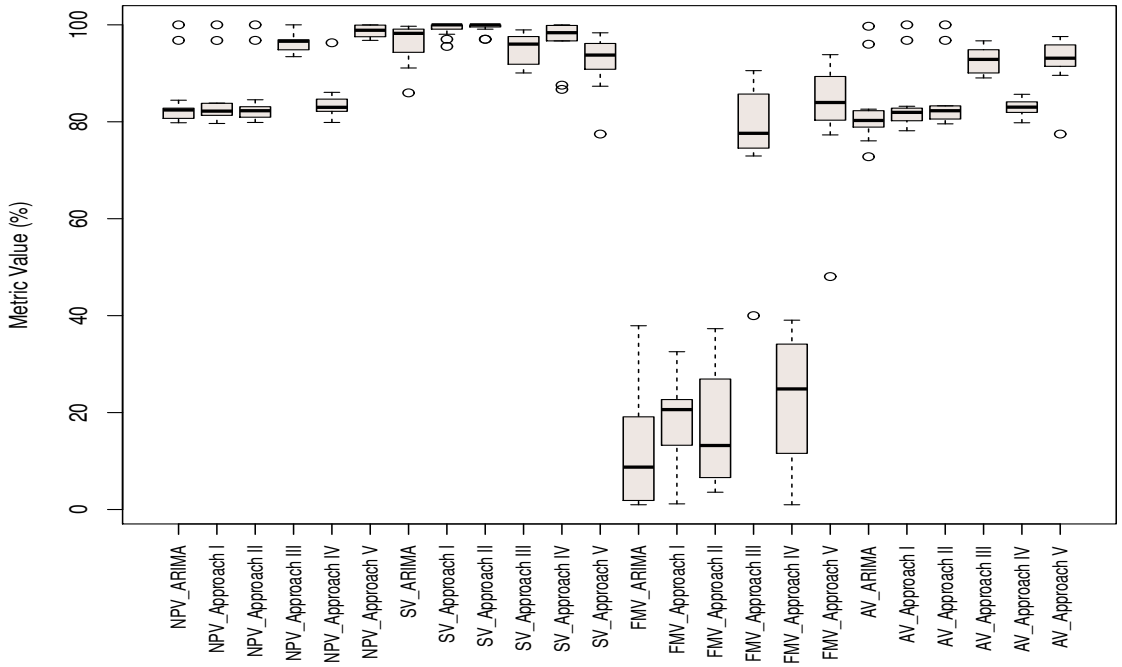


Figure 8.12: Boxplots of contingency table-based metrics for nonlinearly dependent time between failures with volatility clustering

	Response Time				Time Between Failures			
	NPV	SV	FMV	AV	NPV	SV	FMV	AV
ARIMA	93.49	97.85	10.29	92.03	84.29	96.32	12.30	82.17
Approach I	93.75	99.02	22.58	92.93	84.38	99.13	18.03	82.94
Approach II	93.72	99.14	12.59	92.99	84.39	99.43	17.52	83.86
Approach III	98.68	95.07	64.41	94.17	98.71	94.79	77.20	92.47
Approach IV	94.18	98.49	23.93	93.33	84.53	96.47	22.34	84.16
Approach V	99.49	95.62	74.97	95.44	96.32	92.53	82.09	92.62

Table 8.7: Average of contingency table-based metrics for nonlinearly dependent QoS attributes with volatility clustering

- Fourth, the forecasting approach V outperforms all the other forecasting approaches in the negative predictive value, F-measure value, and accuracy metrics. Although this forecasting approach produces relatively the smallest value of specificity metric, this value is still absolutely high, *i.e.* 95.6% and 92.5% in the cases of response time and time between failures respectively.

- ► *The five proposed forecasting approaches and ARIMA model provide high values for the negative predictive value, specificity, and accuracy, and relatively low values for the F-measure value.*
- ► *The forecasting approaches I, II, and IV outperforms the ARIMA model in terms of contingency table-based metrics, especially the F-measure value.*
- ► *Compared to the ARIMA model, the forecasting approaches III and V highly improve the negative predictive value, F-measure value, and accuracy, however, they relatively lose some accuracy in the specificity metric.*
- ► *The forecasting approaches IV and V are not equivalent in terms of contingency table-based metrics, and outperform the other proposed forecasting approaches.*

8.2.3 EQ3. Time Required to Automatically Construct and Use Forecasting Model

The time required for the five proposed forecasting approaches and the baseline ARIMA model to automatically construct and use the forecasting model is computed and depicted in Figures 8.13 and 8.14, respectively. In general, the results in Figure 8.13 show that the five forecasting approaches has different performance in terms of the time required to construct the forecasting model. In particular, the time required by the forecasting approaches I, II, III, IV, and V to construct the forecasting model is on average about 4.0, 3.9, 4.9, 6.9, and 10.1 seconds, respectively, compared to 2.0 seconds required by the baseline ARIMA model. The Mann-Whitney test reports that the time required by the forecasting approaches is significantly different, except in the case of the two forecasting approaches I and II (p-value > 0.05). The main justification for this difference is that the more computations the forecasting approach has to do, the more time is required. Fortunately, the construction of the forecasting model can be done only in the beginning, after triggering adaptations, or as required and planned by the system management. It is worth mentioning that another observation can be reported that the number of observations and time required to construct the forecasting model are linearly correlated. In other words, more historical observations are used to construct the forecasting model more time is required.

Regarding the time required to use the constructed model in order to forecast future QoS values, the results in Figure 8.14 indicate that it is very small and almost the same on average for the five proposed forecasting approaches. More precisely, each one of the five forecasting approaches requires on average about 20 milliseconds to use the constructed model compared to 15 milliseconds required by the baseline ARIMA model. The justification of this result is that the constructed model is used by only substituting the new obtained QoS value in the equation without more computations. Although the Mann-Whitney test reports that the difference in the required time is insignificant (p-values > 0.05), the variation of that time is relatively

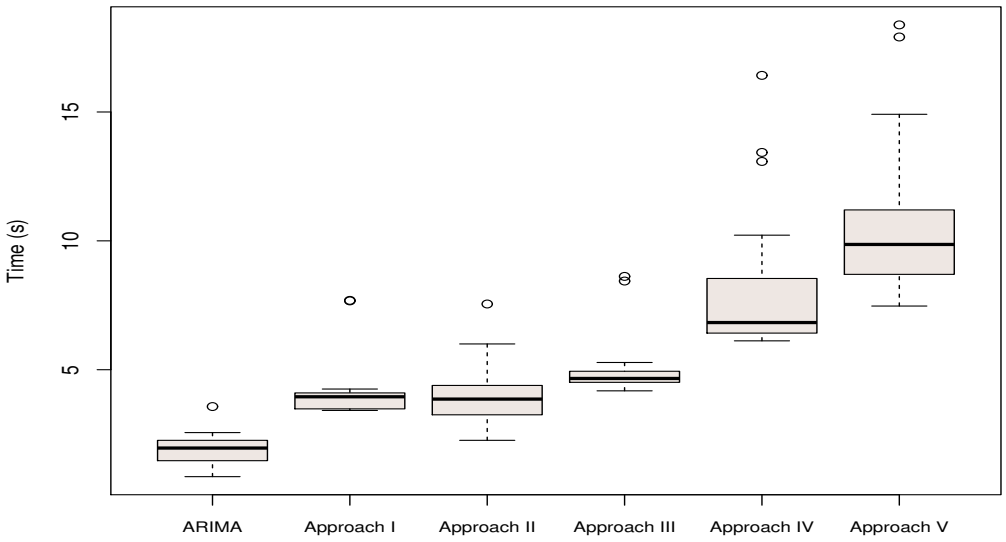


Figure 8.13: Boxplots of time required to construct the forecasting model

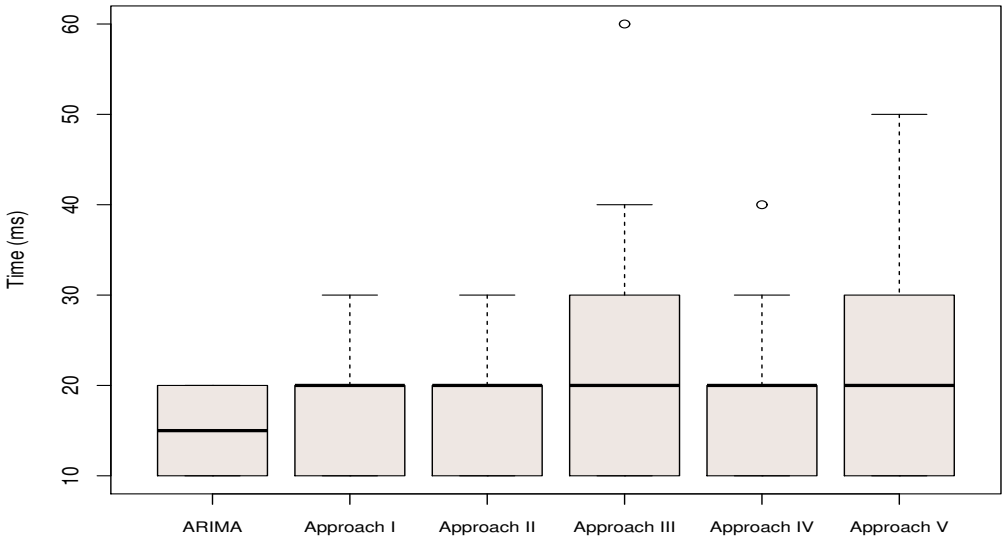


Figure 8.14: Boxplots of time required to use the forecasting model

very high in the case of the two forecasting approaches III and V as evident in Figure 8.14.

- *The five proposed forecasting approaches require on average about 4 to 10 seconds to construct the forecasting model compared to 2 seconds required by the ARIMA model.*
- *The five proposed forecasting approaches require on average about 20 milliseconds to use the constructed forecasting model compared to 15 milliseconds required by the ARIMA model.*

8.3 Discussion and Threats to Validity

8.3.1 Discussion

Based on the detailed results introduced in Section 8.2, the main general points regarding the accuracy and performance of the proposed forecasting approaches as well as their comparison and real applicability can be clearly highlighted in this section.

■ *Accuracy and performance trade-off.* The results show that the forecasting approaches improve the forecasting accuracy by decreasing the MAPE value; however, the cost is that more time is required to construct the forecasting model. In particular, the forecasting approach V achieves the highest accuracy improvement, and in the same time requires more time to construct the model, *e.g.* it requires about 15 seconds (in the case of 500 observations) compared to 2 and 4 seconds required by the baseline ARIMA model and the forecasting approach I, respectively. Moreover, for the same forecasting approach, some accuracy improvement can be achieved by increasing the number of observations required to construct the model; however, this will eventually increase the required time. Therefore, it can be generalized that the more forecasting accuracy improvement, the more time required to construct

the forecasting model. Fortunately, the positive point is that the construction of the forecasting model can be conducted in the beginning and after each adaptation or as planned by the system management. In addition, the using of the constructed model requires small time, which is most likely less than 50 milliseconds.

■ *Contingency table-based metrics trade-off.* The results highlight that the proposed forecasting approaches generally improve the forecasting accuracy of QoS violations compared to the baseline ARIMA model. However, the approaches individually improve differently the contingency table-based metrics. More precisely, the forecasting approaches I, II, and IV achieve small improvement in the negative predictive value, specificity, and accuracy metrics and moderate improvement in the F-measure value metric compared to the baseline ARIMA model. On the other hand, the forecasting approaches III and V achieve high improvement in the negative predictive value, F-measure value, and accuracy metrics and, however, lose some accuracy in the specificity metric compared to the other proposed forecasting approaches and the baseline ARIMA model. This implies that selecting the forecasting approach to be used is not only based on the MAPE value but also based on the contingency table-based metric preferred to be improved. Indeed, this point is extremely related to what the system management needs to optimize: reducing the chance of unnecessary adaptations.

■ *Wavelet-based forecasting approaches and nonlinearity approximation.* An important observation can be highlighted that in the case of nonlinearly dependent QoS attributes with volatility clustering the forecasting approaches III and IV provide equivalent forecasting accuracy, *i.e.* equivalent MAPE value. As introduced in this thesis, the forecasting approach III is based on the wavelet analysis, ARIMA and GARCH models, and on the other hand the forecasting approach IV is based on the SETARMA and GARCH models. Therefore, this implies that the integration of wavelet analysis and linear time series models, *i.e.* ARIMA models, can highly approximate the nonlinearity characteristic of QoS attributes. Actually, this approximation provides some advantages as follows:

- Although the two forecasting approaches III and IV provide the same forecasting accuracy of QoS values in terms of MAPE metric, they individually improve differently the contingency table-based metrics. Indeed, this allows the system management to select one of these approaches that improves the preferred contingency table-based metrics, with an equivalent MAPE value will be produced. Moreover, the system management can use the two forecasting approaches together to simultaneously improve different contingency table-based metrics.
- The forecasting approach III can be used to provide acceptable accuracy level in the cases that the system management needs to forecast the future values of nonlinearly dependent QoS attributes with volatility clustering and, however, requires less time to construct the forecasting model. Because the forecasting approach III requires on average about 5 seconds (for 500 observations) to construct the forecasting model compared to about 7 and 10 seconds required by the forecasting approaches IV and V, respectively.

■ *Forecasting accuracy of response time and time between failures.* The results show that the forecasting approaches generally provide higher forecasting accuracy of the response time than that of the time between failures. By investigating this point, it can be reported that the reasons are:

- The number of observations that are used to construct the forecasting model in the time between failures datasets is much smaller than that in the response time datasets. In fact, most of the number of observations in the time between failures datasets is less than 200 compared to 500 observations in the response time datasets. In literature, researchers [147, 148] propose that online testing can be used to collect more failures data that eventually can increase the number of observations in the time between failures datasets.
- For equal number of observations in both response time and time between failures datasets, we have investigated their serial dependency structure in terms of the ACF and PACF and found that the response time data is more autocor-

related than the time between failures data. In particular, the response time data is significantly autocorrelated up to time lag 4, while the time between failures data is significantly autocorrelated up to time lag 2. Obviously, significant autocorrelation up to higher-order lags increases the forecasting accuracy for the given QoS data.

■ *Applicability of the proposed forecasting approaches.* After discussing the results of the accuracy and performance of the proposed forecasting approaches, the last point is how these forecasting approaches can be used in reality. Actually, using one of the proposed forecasting approaches in real applications can be achieved in different ways or settings as follows. First setting can be that in the beginning statistical tests are used to evaluate the volatility clustering and nonlinearity of the given QoS dataset, and based on the evaluation result and preferred accuracy and performance levels the appropriate forecasting approach can be used. For example, if the evaluation result shows that the given QoS dataset is nonlinearly dependent with volatility clustering and it is required to construct the forecasting model in less time, then the forecasting approach IV can be the appropriate for this case. Second setting can be that in the beginning all the proposed forecasting approaches are applied for the given QoS dataset and their accuracy and performance are evaluated, and the best one in terms of evaluated accuracy and performance is selected and used.

8.3.2 Threats to Validity

The threats to *internal validity* include the QoS datasets being used to evaluate the accuracy and performance of proposed forecasting approaches as well as the statistical tests being used to analyze forecasting results. To reduce the impact of these threats we have considered response time and time between failures datasets of real-world Web services to reflect a realistic situation of QoS attributes. In addition, we have used non-parametric tests to analyze the results and address the evaluation questions, where no statistical constraints are imposed on the forecasting results.

On the other hand, *external validity* is threatened if obtained results cannot be

generalized. Although we have applied the proposed forecasting approaches for the response time and time between failures datasets of several real-world Web services belonging to different domains, further applications to other software systems and Web services are desirable. Additionally, we focus only on response time and time between failures, and the generalizations to other QoS attributes should be considered in future studies. For example, similarly to the response time, the forecasting approaches can be straightforwardly applied to the throughput and CPU utilization as performance metrics. In addition, the forecasting approaches can be extended to be applied to other observable qualities such as availability and accessibility.

8.4 Summary

In this chapter, we evaluated the accuracy and performance of the proposed forecasting approaches and compared them to those of the baseline ARIMA models. This evaluation is achieved by applying the proposed forecasting approaches and baseline ARIMA models to the collected QoS datasets, and then computing the MAPE metric as a measure for the accuracy of forecasting QoS values, contingency table-based metrics as a measure for the accuracy of forecasting QoS violations, and time required to constructed and use the time series model as a measure for the performance. We concluded from the results that while the proposed forecasting approaches improve the forecasting accuracy by decreasing the MAPE value, the cost is that more time is required to construct the forecasting model. In addition, the forecasting approaches generally improve the forecasting accuracy of QoS violations compared to the baseline ARIMA model, however, they individually improve differently the contingency table-based metrics. Moreover, the forecasting approaches generally provide higher forecasting accuracy of the response time than that of the time between failures.

Chapter 9

Conclusion

This thesis has focused on forecasting QoS attributes and proactively detecting potential violations. The work achieved in this thesis includes evaluating the stochastic characteristics of QoS attributes especially response time and time between failures, specifying the class of adequate time series models, proposing an automated procedure for automatically constructing at runtime the forecasting model to fit and forecast QoS attributes, and finally introducing statistical control charts and accuracy measures to continuously evaluate the adequacy and accuracy of the constructed forecasting model in order to provide high QoS forecasting accuracy. The outcome of this work is a collection of QoS characteristic-specific forecasting approaches that taken together constitute a general automated forecasting approach for QoS attributes. Therefore, this thesis addresses the limitations of the existing approaches based on time series modeling and contributes to the state of the art of the proactive approaches that support proactive SLA management, proactive service selection and composition, and proactive adaptation of Web services or service-based systems. In the following, the main contributions of the thesis are highlighted in detail, followed by a discussion of future work that could be done to further improve the proposed forecasting approaches.

Contributions

The research work presented in this thesis has made a contribution to providing accurate forecasting for QoS values and their potential violations. In particular, the research work that has been achieved includes the following tasks.

1. Real-world Web services have been invoked over an extended period, datasets for response time and time between failures have been constructed, and then appropriate statistical methods/tests have been applied to these collected QoS datasets in order to evaluate the stochastic characteristics of QoS attributes. These QoS stochastic characteristics include probability distribution, serial dependency, stationarity, and nonlinearity.

2. The class of adequate time series models has been specified for the QoS attributes by classifying the evaluated QoS stochastic characteristics into two groups. One is related to the underlying assumptions of time series modeling, namely probability distribution, serial dependency, and stationarity (in the mean). The other group specifies the class of adequate time series models which are stationarity (in the variance) and nonlinearity. Accordingly, four types of the stochastic characteristics of QoS attributes have been identified and for each type the class of adequate time series models has been specified.

3. Based on the well-established Box-Jenkins methodology, an automated procedure has been developed for automatically constructing time series models. This proposed procedure addresses the human intervention issue that inherently exists in the Box-Jenkins methodology.

4. The statistical control charts and accuracy measures have been introduced to be used to continuously evaluate the adequacy and accuracy of the constructed time series model, respectively, in order to guarantee high QoS forecasting accuracy.

The outcome of achieving these tasks is a collection of QoS characteristic-specific automated forecasting approaches based on time series modeling. Each one of these

forecasting approaches is able to fit and forecast only a specific type of the stochastic characteristics of QoS attributes (out of the four types mentioned above), however, the forecasting approaches together will be able to fit different dynamic behaviors of QoS attributes and forecast their future values. Consequently, these forecasting approaches will together provide a basis for a general automated forecasting approach for QoS attributes.

Accordingly, the research work presented in this thesis contains following novel contributions.

- The stochastic characteristics of QoS attributes of real-world Web services have been evaluated. This evaluation is based on QoS datasets, especially response time and time between failures, of real-world Web services belonging to different applications and domains. The evaluation results show that most of the response time and time between failures qualities are serially dependent over time and the non-stationarity in the variance (*i.e.* volatility clustering) and nonlinearity are two important characteristics which have to be considered while proposing QoS forecasting approaches.

- An automated statistical forecasting approach has been proposed for nonlinearly dependent QoS attributes. This forecasting approach (called forecasting approach I) is based on SETARMA time series models, and it is able to effectively fit the nonlinear dynamic behavior of QoS attributes and accurately forecast their future values and potential violations. The evaluation results showed that the forecasting approach I outperforms the baseline ARIMA model in forecasting the QoS values and potential violations. In particular, for forecasting Qos values, the forecasting approach I improves the forecasting accuracy of about 21.4% and 23% for the response time and time between failures, respectively. In addition, for forecasting QoS violations, the forecasting approach I achieves small relative improvement for the negative predictive value, specificity, and accuracy metrics; however, it achieves the highest improvement (about 61.7% and 47.0%) for the F-measure value in the cases of response time and time between failures, re-

spectively. Moreover, the results showed that the forecasting approach I requires about 4 seconds to construct the forecasting model and about 20 milliseconds to use it compared to 2 seconds and 15 milliseconds, respectively, required by the ARIMA model.

- Two automated statistical forecasting approaches have been proposed for linearly dependent QoS attributes with volatility clustering. The first forecasting approach (called forecasting approach II) is based on ARIMA and GARCH time series models, while the second one (called forecasting approach III) is based on wavelet analysis, ARIMA and GARCH time series models. The evaluation results showed that the two forecasting approaches outperform the ARIMA model in forecasting the QoS values and potential violations. In particular, for forecasting QoS values, the forecasting approaches II and III improve the forecasting accuracy of about 20.3% and 40.5%, respectively in the case of response time, and of about 19.5% and 39.8%, respectively in the case of time between failures. In addition, for forecasting QoS violations, the forecasting approach II achieves small relative improvement for the negative predictive value, specificity, and accuracy metrics; however, it achieves the highest improvement for the F-measure value. On the other hand, the forecasting approach III highly improves the negative predictive value, F-measure value, and accuracy, however, it loses some accuracy in the specificity metric. Moreover, the results showed that the forecasting approaches II and III require about 4 and 5 seconds, respectively, to construct the forecasting model and about 20 milliseconds to use it. This result implies that these two forecasting approaches are not equivalent in terms of accuracy and performance, and means that there is flexibility in using these forecasting approaches according to preferred accuracy and performance levels.

- Two automated statistical forecasting approaches have been proposed for nonlinearly dependent QoS attributes with volatility clustering. The first forecasting approach (called forecasting approach IV) is based on SETARMA and GARCH time series models, while the second one (called forecasting approach V) is based

on wavelet analysis, SETARMA and GARCH time series models. These two forecasting approaches work similarly to the above two forecasting approaches proposed for linearly dependent QoS attributes with volatility clustering except that they construct SETARMA models rather than ARIMA models for the original QoS data or general trend sub-series. 6.9, and 10.1 seconds The evaluation results highlighted that these two forecasting approaches outperform the ARIMA model in forecasting the QoS values and potential violations. For forecasting QoS values, the forecasting approaches IV and V improve the forecasting accuracy of about 27.4% and 50.4%, respectively in the case of response time, and of about 31.6% and 43.3%, respectively in the case of time between failures. In addition, for forecasting QoS violations, the forecasting approach IV achieves small relative improvement for the negative predictive value, specificity, and accuracy metrics; however, it achieves the highest improvement for the F-measure value. On the other hand, the forecasting approach V highly improves the negative predictive value, F-measure value, and accuracy, however, it loses some accuracy in the specificity metric. Moreover, the results showed that the forecasting approaches IV and V require about 7 and 10 seconds, respectively, to construct the forecasting model and about 20 milliseconds to use it. Similarly to the forecasting approaches II and III, the results imply that the forecasting approaches IV and V are not equivalent in terms of accuracy and performance, and thus there is flexibility in using these forecasting approaches according to preferred accuracy and performance levels.

These contributions address the challenges identified in the thesis, which include (1) Evaluating the key stochastic characteristics of QoS attributes based on real-word QoS datasets, which is an essential requirement for proposing an efficient forecasting approach; (2) Specifying the class of adequate time series models that can be used to fit and forecast QoS attributes based on the evaluated QoS stochastic characteristics; (3) Addressing how the specified time series models can be automatically constructed at runtime for the given QoS attribute; and (4) Addressing

how the adequacy and forecasting accuracy of the constructed time series model can be continuously evaluated at runtime. Consequently, this thesis addresses the limitations of the existing proactive approaches based on time series modeling and provides a solution for forecasting QoS attributes and proactively detecting potential violations. Thus, it contributes to the literature of the proactive approaches that support proactive SLA management, proactive service selection and composition, and proactive adaptation of Web services or service-based systems.

Future Work

In this thesis, automated statistical forecasting approaches have been proposed for QoS attributes. However, there is still much work to be done to further improve and enhance these forecasting approaches. In the following, possible future work is introduced.

■ *Extending the accuracy and performance evaluation of the proposed forecasting approaches.* In the current work, only the one-step-ahead forecasts are used to evaluate the forecasting accuracy of the proposed forecasting approaches. With the goal of comparing the accuracy of the proposed forecasting approaches, the one-step-ahead forecasts are initially enough to give simple and fair comparison. However, for future work it is recommended to consider higher-step-ahead forecasts in order to deeply evaluate the accuracy of the proposed forecasting approaches and investigate their ability for long-term forecasting. In addition, considering the required time to construct the forecasting model in relation to the size of model training dataset is an interesting future work for finding a tailored trade-off between the accuracy and performance of the proposed forecasting approaches.

■ *Extending the work to other QoS attributes.* The work in this thesis is limited to response time and time between failures datasets. However, there are some issues related to the time between failures quality need to be addressed in future work. First, the number of historical observations required to construct the forecasting model in the time between failures datasets could be a problem in the practice, in

particular for the high-available Web services with only few failures. Second, failures might occur in bursts. For instance, if the network is down, a lot of sequential requests might be lost. Whereas during the normal operation, almost no failures occur. This case needs to be carefully investigated with the aim of checking how these bursts are observed in the measurements of real-world Web-services and evaluating how they influence the accuracy and performance of the proposed forecasting approaches. On the other hand, the work can be extended to other QoS attributes such as availability and accessibility.

■ *Extending the work to multivariate time series analysis and Bayesian approach.* The possibility of adopting the multivariate time series analysis techniques can be investigated in future rather than using only the univariate time series analysis adopted in this thesis. The multivariate time series analysis will assist in constructing the forecasting model that quantifies the dependency among the different QoS attributes and forecasts their future values in the same time. In addition, the current research work has adopted a non-Bayesian approach to estimate the parameters of the time series models. However, the Bayesian approach can be applied to model estimation thereby exploiting its advantages over non-Bayesian in the domain of QoS forecasting.

■ *Including external factors in the forecasting model to further improve forecasting accuracy.* In the current work, the historical QoS dataset has been used as a time series to construct the forecasting model in order to eventually forecast its future values. However, other external factors such as request rate, input data size, and CPU utilization can be included in the forecasting model as exogenous variables. Including these external factors in the forecasting models can further improve the forecasting accuracy. In addition, the external variables can be used to explain the changes in the QoS levels and to some extent control these levels. This extension for future work may be of particular applicability in the domains related to Cloud services and applications that might require using external factors in order to explain or control the QoS levels. Moreover, the proposed forecasting approaches can be

extended to be applied to the request arrival rate data for load forecasting. In particular, the arrival rate data brings some practical challenges such as seasonal patterns and bursts together with varying aggregation levels and forecast horizons (*e.g.* on-demand provisioning vs. longer-term capacity planning).

Appendix A

The detailed description of real-world Web services that are mentioned in the thesis are introduced in the following Table. This description includes Web service name, functionality description, provider name, and WSDL URL.

Table 9.1: Description of some of the monitored real Web services

WS_{id}	WS Name	Functionality Description	Provider Name	WSLD URL
WS_1	StockQuote	Reports stock quotations for a company by using provided stock symbol.	WebserviceX.NET	`http://www.webservicex.com/stockquote.asmx`
WS_2	YahooQuoteWebService	Gets delayed stock information from Yahoo by using provided stock symbol.	datasprings.com	`http://www.datasprings.com/desktopmodules/stock%20quotes/dataspringsstocksearch.asmx`
WS_3	HolidayService	Calculates national holidays for the provided country code.	holidaywebservice.com	`http://www.holidaywebservice.com/Holidays/HolidayService.asmx`

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Table 9.1 – Continued

WS_{id}	WS Name	Functionality Description	Provider Name	WSLD URL
WS_4	PhoneNotify	Delivers on-demand voice notifications, including alerts and two-way interactive voice messaging.	CDYNE Corporation	`http://ws.cdyne.com/notifyws/phonenotify.asmx`
WS_5	GetAuditInfo	Gets some infromation about executing an operation of a system as well as users information such as user, name, password, date, and time.	topfo.com	`http://manage.topfo.com/GetAuditInfo.asmx`
WS_6	SmsSend2	Sends two-way SMS messages.	utnet.cn	`http://sms.utnet.cn/smsservice2/v2/smssend2.asmx`
WS_7	Research	Research service in Microsoft Office 2003 provides a definition, a synonym, facts about a company's finances, an encyclopedia article, or other types of information from the Web.	microsoft.com	`http://office.microsoft.com/research/query.asmx`
WS_8	TiempoService	Used by transportesjoselito.com to get the time.	transportesjoselito.com	`http://www.transportesjoselito.com/atlas/modal/TiempoService.asmx`

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Table 9.1 – Continued

WS_{id}	WS Name	Functionality Description	Provider Name	WSLD URL
WS_9	Doc	Used by shuaiche.com to implement a set of document style interop operations.	shuaiche.com	`http://www.shuaiche.com/ws/Doc.asmx`
WS_{10}	Service1	Used by visualprog.cz as authentication service in order to allow clients to get a globally unique identifier (GUID) from the database by using their login names and passwords.	visualprog.cz	`http://visualprog.cz/Database/service1.asmx`
WS_{11}	AjaxWS	Used by cnblogs.com to collect users comments and questions.	cnblogs.com	`http://www.cnblogs.com/WS/AjaxWS.asmx?WSDL`
WS_{12}	BookStoreService	Provides the list of the books according to author, title, price and chckes for their availability.	tempuri.org	`http://dotnet.jku.at/csbook/solutions/19/BookStoreService.asmx`
WS_{13}	ValidateCodeWebService	Supports codes validation including Chinese letters, numbers, images and multimedia.	webxml.com.cn	`http://www.webxml.com.cn/WebServices/ValidateCodeWebService.asmx`
WS_{14}	TraditionalSimplifiedWebService	Provides conversion of simplified Chinese from/to traditional Chinese.	webxml.com.cn	`http://www.webxml.com.cn/WebServices/TraditionalSimplifiedWebService.asmx`

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Table 9.1 – Continued

WS_{id}	WS Name	Functionality Description	Provider Name	WSLD URL
WS_{15}	SharepointEmailWS	Is sharepoint email integration Web service that creates, modefies, and deletes contacts and groups details.	perihel.hr	`http://www.perihel.hr/_vti_bin/SharepointEmailWS.asmx`
WS_{16}	People	Used by perihel.hr to check claims and search and resolve prinipals.	perihel.hr	`http://www.perihel.hr/_vti_bin/People.asmx`
WS_{17}	WebService	Used by I-dno to get information about cities, provinces, and villages in China.	i-dno.com	`http://i-dno.com/WebService.asmx`
WS_{18}	ValidateEmailWebService	validates e-mail address by looking up the given e-mail domain and mail server to send data to determine the e-mail address is correct or not.	webxml.com.cn	`http://www.webxml.com.cn/WebServices/ValidateEmailWebService.asmx`
WS_{19}	StockInfoWS	Is a Chinese timely stock market data Web Service that supports Hong Kong, Shenzhen and Shanghai stock funds, bonds and equities.	webxml.com.cn	`http://www.webxml.com.cn/WebServices/StockInfoWS.asmx`

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Table 9.1 – Continued

WS_{id}	WS Name	Functionality Description	Provider Name	WSLD URL
WS_{20}	GeoIPService	Enables the user to easily look up countries by IP address / Context.	webservicex.com	`http://www.webservicex.com/geoipservice.asmx`
WS_{21}	GlobalWeather	Is free Web Service that provides the current weather and along with additional information for major cities (with airport) around the world.	WebserviceX.NET	`http://www.webservicex.com/globalweather.asmx`
WS_{22}	UKLocation	Gets UK Postcode,Town, and County and Validates UK Address as well.	webservicex.com	`http://www.webservicex.com/uklocation.asmx`
WS_{23}	ABA	Allows the user to validate United States bank routing numbers (ABA numbers) or search for a participant bank by phone number or bankname/city/state.	webservicex.com	`http://www.webservicex.com/aba.asmx`
WS_{24}	EnglishChinese	Is a Chinese $< - >$ English bidirectional translation Web service.	webxml.com.cn	`http://fy.webxml.com.cn/webservices/EnglishChinese.asmx`
WS_{25}	wsRegistroLog	Used by CCNI shipping company for registration and login.	ccni.cl	`http://www1.ccni.cl/wsRegistroLog/ws/services/wsRegistroLog?wsdl`

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Table 9.1 – Continued

WS_{id}	WS Name	Functionality Description	Provider Name	WSLD URL
WS_{26}	NWIS	Provides access for retrieving data from the USGS National Water Information System (NWIS) that contains millions of sites measuring streamflow, groundwater levels, and water quality.	tempuri.org	`http://river.sdsc.edu/NWISTS/nwis.asmx`
WS_{27}	OrteLookup	Retreives the names of German cities starting with a specific string.	mathertel.de	`http://mathertel.de/AJAXEngine/S02_AJAXCoreSamples/OrteLookup.asmx`
WS_{28}	AutRegService	Used by sst.dk to report the availability of health professionals and specialities.	sst.dk	`http://autregwebservice.sst.dk/autregservice.asmx`
WS_{29}	MobileCodeWS	Provides the latest domestic phone number attribution, and its data is updated monthly.	webxml.com.cn	`http://www.webxml.com.cn/WebServices/MobileCodeWS.asmx`
WS_{30}	SendSMSWorld	Sends free SMS to a limited set of providers in certain countries.	webservicex.com	`http://www.webservicex.com/sendsmsworld.asmx`

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Table 9.1 – Continued

WS_{id}	WS Name	Functionality Description	Provider Name	WSLD URL
WS_{31}	country	Gets more information about a country (e.g. country name, country code, international dialing code, currency name, currency code, greenwich mean time, etc.).	WebserviceX.NET	http://www.webservicex.net/country.asmx
WS_{32}	BdcWebService	Is a business data catalog metadata Web service used by forums.genom-e.com.	forums.genom-e.com	http://forums.genom-e.com/_vti_bin/BusinessDataCatalog.asmx
WS_{33}	IpAddressSearchWebService	Is IP Address Search WEB service which includes IP address data known in China and abroad as the most complete IP address data, where the number of records is now over 370,000 and continues to update.	webxml.com.cn	http://www.webxml.com.cn/WebServices/IpAddressSearchWebService.asmx
WS_{34}	ChinaTVprogramWebService	Provides online access to Chinese television stations.	webxml.com.cn	http://www.webxml.com.cn/webservices/ChinaTVprogramWebService.asmx
WS_{35}	C_InfoService	Used by wanguoschool.net to add and get articles hits.	wanguoschool.net	http://www.wanguoschool.net/DesktopModules/C_Info/WebService/C_InfoService.asmx

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Table 9.1 – Continued

WS_{id}	WS Name	Functionality Description	Provider Name	WSLD URL
WS_{36}	kiteservice	Used by kitesoft.cn to get a location by IP addrress.	kitesoft.cn	http://www.kitesoft.cn/services/kiteservice.asmx
WS_{37}	ChinaStockWebService	Reports timely Chinese stock market data (stock name, price, ...).	webxml.com.cn	http://www.webxml.com.cn/WebServices/ChinaStockWebService.asmx?wsdl
WS_{38}	projname	Used by hzn.secondhouse.soufun.com hzn.secondhouse.soufun.com to manage the existing projects including getting the names, codes, and purposes of the projects.	hzn.secondhouse.soufun.com	http://hzn.secondhouse.soufun.com/HouseService/Estimate/projname.asmx?wsdl
WS_{39}	WeatherWebService	Reports weather for major cities in china.	webxml.com.cn	http://www.webxml.com.cn/WebServices/WeatherWebService.asmx?WSDL
WS_{40}	ChinaZipSearchWebService	Enables to search in a database contains all the zip code total of 187,285 records, which is the most complete China zip code data.	webxml.com.cn	http://www.webxml.com.cn/WebServices/ChinaZipSearchWebService.asmx?wsdl
WS_{41}	WSMusic	Provides different type of music and songs.	microsoft.com	http://ws.contentlib.mweb.co.th/ContentLibrary.WS/WSMusic.asmx

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Table 9.1 – Continued

WS_{id}	WS Name	Functionality Description	Provider Name	WSLD URL
WS_{42}	AmazonBox	Uses Amazon.com Web Services to return a string formatted HTML table with up to 9 product links and their associated prices, images, and manufacturers. All boxes need only a single string input value. An empty HTML table is returned if no results can be retrieved. See the list below for box types and input examples.	xmlme.com	`http://www.xmlme.com/WSAmazonBox.asmx`
WS_{43}	CopyDanService	Using ISSN number returns weather the article is a scientific and therefore subject to the agreement.	statsbiblioteket.dk	`http://webservice.statsbiblioteket.dk/ws-ekopicopydan/services/CopyDanServicePort?wsdl`
WS_{44}	RodeoWebService	Used by Lemontech company, which is specialized in project development Web-based computing, to collect information about Web services and classify them in major lists and groups.	lemontech.cl	`http://rodeo.lemontech.cl/rodeo/app/webservices.php?wsdl`

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Table 9.1 – Continued

WS_{id}	WS Name	Functionality Description	Provider Name	WSLD URL
WS_{45}	TrainTimeWebService	Provides different train schedules and stations.	webxml.com.cn	`http://www.webxml.com.cn/WebServices/TrainTimeWebService.asmx`

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