# Cloud-Centric Real-Time Anomaly Detection Using Machine Learning Algorithms in Smart Manufacturing

by

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# Abstract

Manufacturing is the backbone of a country's gross domestic product (GDP). With an ever-growing population, demand for goods manufacturing has increased exponentially. Efficient manufacturing has been the primary aim since the beginning. The performance of real-time manufacturing requires an efficient and reliable system. Globally, manufacturing accounts for 16% of GDP and 14% of employment. The manufacturing sector contributes up to $100 billion annually to the GDP as per the Australian Bureau of Statistics, 2019. In the manufacturing sector, in 2019, 23.5% of business expenditure was attributable to research and development.

In all forms, the manufacturing industry is in dire conditions with traditional practices resulting in inefficiencies. These traditional practices resulted in inefficiencies due to i) rework and rejigging, ii) uncontrolled production, iii) miscommunications and mismanagements, iv) lack of decision-making, v) ambiguity due to manual handling and vi) increased inventory. In addition, personalised product demands with growing competitiveness require agile manufacturing with just-in-time delivery to avoid large stocks of inwards and outwards inventory. Manufacturing systems inherit multidisciplinary approaches and, therefore, require integrated solutions to avoid miscommunication and indecision. Further, manufacturing typically comprises convoluted and heterogenous operations. Characterising and connecting these operations in an integrated manufacturing system is an overarching problem; for example, there can be a disconnect between enterprise resource planning (ERP) and manufacturing execution systems (MES). In recent years, smart manufacturing (SM) has shown potential for its ability to address the aforementioned challenges. However, there has been a lack of adoption and implementation of SM due to challenges in technological integration to harness the required benefits. To compound this complexity, the affordance of integrated SM is an additional challenge for SMEs (in Australia, small and medium enterprises comprise 60% to 70%). The exorbitant costs of SM technologies, skilled human resources and associated regular upgrades are factors contributing to the poor uptake.

In the present research, a SM framework that integrates ERP and MES for enhanced efficiencies, decision-making and low-volume manufacturing is developed. A plethora

of transformative technologies are integrated in SM framework, including a cloud computed (CC) digital twin (DT) paradigm for controlled accessibility from various disciplines. Further, DT provided unique visualisation and augmentation capabilities for manufacturing mock-ups and upskill training, while a decision matrix dashboard was developed in an SM framework using machine learning (ML). SM-based tools, such as ML, CC and DT, enhance efficiencies while reducing errors and improving analytics for decision frameworks. In this research, the development of a cyber–physical system (CPS) integrated with AR and VR connected through cloud platforms is also proposed. AR and VR are encompassed in a SM framework and provide adaptive nature and enhancements in decision-making with real-time seamless data analysis from ERP to manufacturing and vice versa. The research initially characterised heterogeneous operations within a textile machinery (e.g., cutting machines). Operational data were accumulated using sensors and programming from a physical system (e.g., using apparent power and real power). The cyber system was subsequently developed using AR and VR technologies for enhanced visualisations with cloud integration. The cloud-integrated system communicated to the CPS environment bidirectionally. Data were analysed for improved efficiency and reduced errors (e.g., optimal takt using ML algorithms, such as isolation tree or K-nearest neighbour [KNN]). The use of the CPS system improved the personalised product development with added value, and decision-making was enhanced by predictions and self-corrections embedded through ML. Further, the present research validated the SM framework by implementing a cloud-centric paradigm in the textile industry to improve performance and demonstrate efficacy in an SM environment.

The SM framework developed in this research was validated with a case study on textile manufacturing and led to the following outcomes when compared with traditional manufacturing: i) efficiency gains of over 31%, and ii) decision framework established 18% of cost and 31% of time (overall inefficiencies were reduced by 40% compared with traditional manufacturing in terms of decision-making) and iii) unique agility related to low-volume personalised product manufacturing, such as automated packing, automated product tracking and embedded intelligent agile operational capabilities. This research produced a SM framework and successfully implemented it in the context of the textile manufacturing industry. The framework could be adopted in other manufacturing contexts to harness enhanced efficiencies while improving decision-making and agility.

**Key words:** smart manufacturing, machine learning, digital twin, cloud computing, augmented reality, virtual reality, and cyber physical system.

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# Declaration

I declare that the thesis presented represents my own work and has not been previously submitted to any other institution but to the completion of the Doctor of Philosophy program in engineering. I acknowledge to the best of my understanding that the research presented contains no previously submitted content, with the exception of proper recognition being made.

Sourabh Dani, February 2022

# Preface

Main contributions:

i) **Sourabh Dani**, Jiong Jin and Ambarish Kulkarni, ‘Current state of art industry survey in Industry 4.0 manufacturing industries’, submitting for Journal of Industrial Engineering and Management (under review) March 2022.

ii) **Sourabh Dani**, AK Rahman, Jiong Jin, and Ambarish Kulkarni, ‘Real-time Cloud Empowered VMS’, published for the special edition of ‘Handbook of Real-time Computing’, Springer published April 2022.

iii) **Sourabh Dani**, Jiong Jin and Ambarish Kulkarni, ‘Comprehensive survey of Real-time anomaly detection in High Dimensional Data in Manufacturing scenario’, submitted to the IEEE International Conference on Cloud Computing (under review) March 2022.

iv) **Sourabh Dani**, Jiong Jin and Ambarish Kulkarni, ‘Real-Time Anomaly Detection in Smart Manufacturing System’ conference on Industrial Connectivity for a manufacturing process using Cyber-Physical Systems (under review) April 2022.

v) **Sourabh Dani**, AK Rahman, Paul Shuva, Jiong Jin, and Ambarish Kulkarni, ‘Cloud Empowered High Dimensional Anomaly Detection’, submitted to the international journal of IEEE (impact factor: 3.367) March 2022.

*Dedicated to my parents, two lovely sisters and my better half*

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# Abbreviations

| | |
|---|---|
| ***2D*** | Two Dimensional |
| ***3D*** | Three Dimensional |
| ***ABS*** | Australian Bureau of Statistics |
| ***ACSC*** | Aggregated Cyber Space Controller |
| ***AD*** | Anomaly Detection |
| ***AI*** | Artificial Intelligence |
| ***AM*** | Additive Manufacturing |
| ***AMCoT*** | Advanced Manufacturing Cloud of Things |
| ***AR*** | Augmented Reality |
| ***AS*** | Australian Standards |
| ***AVM*** | Automatic Virtual Metrology |
| ***AVR*** | Augmented Virtual Reality |
| ***BOM*** | Bill of Material |
| ***CAD*** | Computer Aided Design |
| ***CC*** | Cloud Computing |
| ***CI*** | Continuous Integration |

| | |
|---|---|
| ***CNR*** | Cloud Networked Robotics |
| ***CPS*** | Cyber Physical System |
| ***DL*** | Deep Learning |
| ***DOE*** | Design of Experiment |
| ***DT*** | Digital Twin |
| ***GDP*** | Gross Domestic Product |
| ***HD*** | High Dimensional |
| ***IaaS*** | Infrastructure as a Service |
| ***IEEE*** | Institute of Electrical and Electronics Engineers |
| ***I-MS*** | Innovative Manufacturing Systems |
| ***IoT*** | Internet of Things |
| ***IR*** | Infrared Sensor |
| ***KNN*** | K-Nearest Neighbour |
| ***LOGR*** | Logistic Regression |
| ***LPB*** | Laser Power Bed |
| ***LR*** | Linear Regression |
| ***LSTM*** | Long Short-Term Memory |

| | |
|---|---|
| ***ML*** | Machine Learning |
| ***MLR*** | Multiple Linear Regression |
| ***MR*** | Mixed Reality |
| ***PaaS*** | Platform as A Service |
| ***PAM*** | Pluggable Application Module |
| ***PM*** | Predictive Maintenance |
| ***PR*** | Polynomial Regression |
| ***PS*** | Physical Shopfloor |
| ***PSDC*** | Physical Space Distributed Controller |
| ***RA*** | Regression Analysis |
| ***RFR*** | Random Forest Regression |
| ***RMS*** | Root Mean Square |
| ***SaaS*** | Software as A Service |
| ***SKU*** | Stock Keeping Unit |
| ***SVM*** | Support Vector Machine |
| ***SVR*** | Support Vector Regression |
| ***TA*** | Task Analysis |
| ***VLSTM*** | Variational Long Short-Term |

| | |
|---|---|
| | Memory |
| ***VR*** | Virtual Reality |
| ***VS*** | Virtual Shopfloor |

# 1 Thesis overview

## 1.1 Introduction

Manufacturing is a mixture of formulation or biological processing using labour, machinery and ever-more-advanced tools. Traditional manufacturing systems were based on quality production and were intensive on cost competitiveness and flexibility within manufacturing. Demand for quality products is continually increasing. There are increased expectations from manufacturers, such as for individualisation or personalised products, environmental stability, zero accidental zones and reduced energy consumption. To fulfill market demands and ensure sustainability with the above-mentioned standards, manufacturing systems demand continuous improvement. Smart manufacturing (SM) is seen as the potential upgrade needed by existing manufacturing systems. SM consists of a strategical paradigm that comprises several advanced technologies to fulfill requirements. SM incorporates advanced technological trends, such as machine learning (ML), cyber physical systems (CPS) and cloud computing (CC). The use of these technologies in manufacturing has led to remarkable changes and has strengthened the manufacturing industry in a global context. Researchers have also considered the challenges involved in raising manufacturing standards, implementing ML algorithms and comparing current practices with the proposed SM framework.

This chapter first discusses the research problems and outlines the research aim and objectives. A section supporting the statements is subsequently included to highlight the novelty of the research. Lastly, this chapter ends with the thesis organisation section, which provides a brief insight into the contents of the thesis.

## 1.2 Research Background

Manufacturing is the process of converting raw materials into ready-to-consume goods. The family manufacturing system encompasses every industry, such as the food, wood, textile, metal, plastic and medical industries. These industries have one thing in common—machinery and human intervention. The machinery used in these industries exhibits distant and complex behaviours. In conjunction with ever-escalating amounts of digital data, the need for automated approaches to data analysis continues to grow. ML algorithms have been used to develop methods that instinctively detect data, before using the models to make predictions or estimate the consequences of activities. Thus, ML is considered a relative field of data extraction, statistics and mining, though it varies in terms of prominence and terminology. ML and CC have been used in various CPS for several decades, including in Industry 4.0, healthcare, agriculture and farming, construction and development, while many further sectors use ML and CC. These techniques help reduce the costs of manufacturing and improve performance in terms of quality, quantity, time to reach market and product branding.

Measures that improve quality and reduce manufacturing times help manufacturers to meet the expectations of the market. Manufacturing plays a significant role in the gross domestic product (GDP) of countries around the world. Research conducted in 2019 showed that Australian manufacturing had the sixth-largest economic impact, while the country had the seventh-largest employment industry (ABS, 2019). In 2019, manufacturing in Australia accounted for 11% of annual export earnings and had significant contributions to research investment compared to other industries (Moustafa, Turnbull, & Choo, 2019). The sector comprised nearly 47,000 companies and employed close to one million people. According to research by the Australian Trade and Investment Commission, since 1992, Australia has experienced substantial annual economic growth globally among all the developed economies. According to the Australian Bureau of Statistics (ABS, 2019). Australia was responsible for ~2% of the world's GDP, accounting for two trillion Australian dollars (see Figure 1). Meanwhile, manufacturing accounted for 9% of the country's overall GDP, of which the textile industry specifically played a significant role.

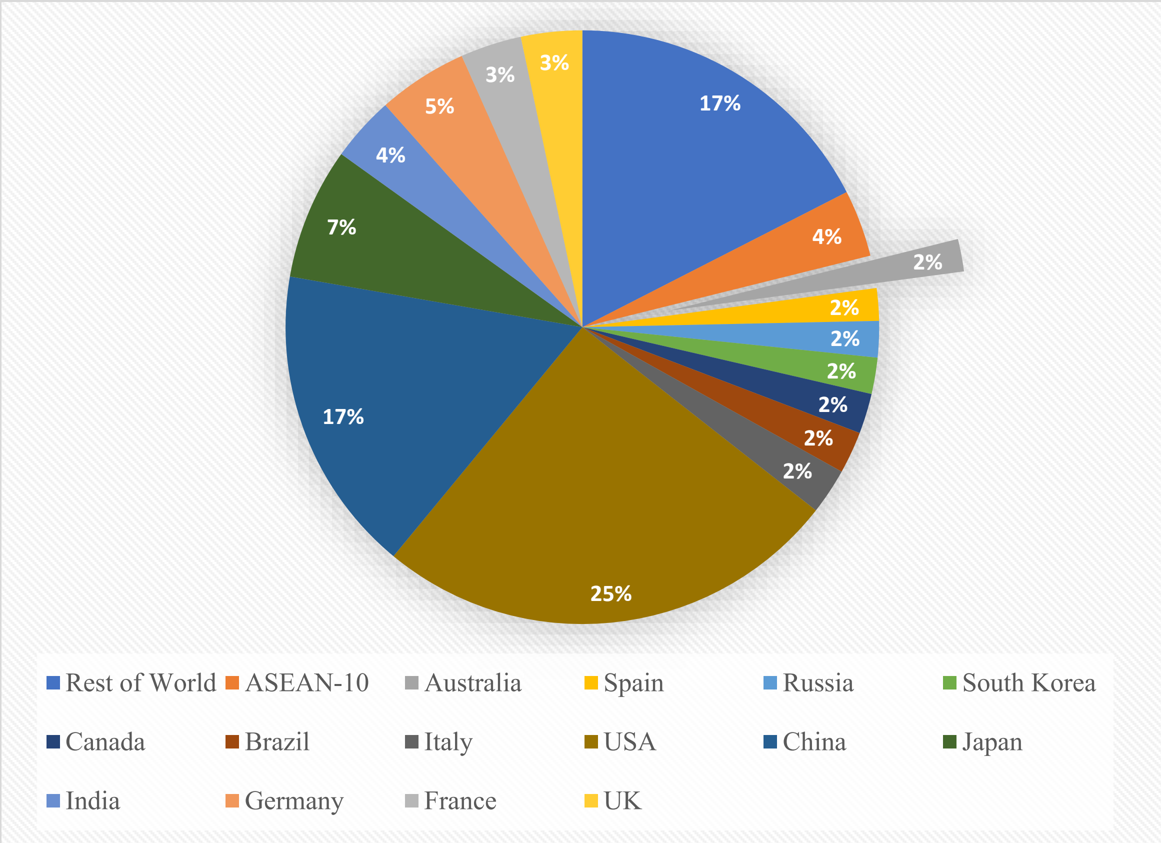


**Figure 1 Australia's contribution in a global context**

Australian manufacturing has faced several challenges, including inefficiencies, high labour costs and reduced export potentials (e.g.: comparatively higher currency exchange rates). Often, the manufacturing paradigm inherits heterogeneous nature with a multi-disciplinary approach. In addition, product manufacturing is influenced by customer demands, most recently for personalised products. Traditional manufacturing practices inherited limitations, such as inefficiencies, waste and negative environmental effects. Compared with many other manufacturing industries, the textile manufacturing industry has the most heterogeneous operations, such as tailoring, cutting, sewing, knitting, lamination and packing, which are operated manually at individual stations. Often, these processes create inefficiencies, wastage, reworking and rejigging. Along with this, communication and decision-making within departments and suppliers are often seen as inadequate, resulting in delays and increased costs. Moreover, the textile industry struggles to meet customer demands for individualised products.

In recent years, manufacturing has been influenced by innovative technologies. Recent exponential growth in advanced tools, such as augmented reality (AR), virtual reality

(VR), ML, predictive analysis and CC has led manufacturing towards smart industrialisation. At present, in all forms, these technologies have been implemented in singularities with a limited benefit to manufacturing industries. The key gap found was integration and seamless real-time integrations of these tools, providing individualised solutions within manufacturing. Deploying these technologies required increased set-up and maintenance costs. Approximately 70% of Australian manufacturing industries comprised of small- and medium-sized enterprises (SMEs) (Geoff Gilfillan Statistics and Mapping Section, 2018). Uptake of these technologies has been slow in manufacturing due to their lack of affordability for SMEs. The novel idea in this research was to harness underlying technologies to integrate cost-effective SM to enhance productivity and decision-making capabilities.

## 1.3 Aim and Objectives

This research aimed to develop a cloud-centric DT paradigm emdedding advanced and improved applied ML algorithms harnessing CPS techniques for enhanced efficiency, decision making and low-volume individualised manufacturing. The research objectives were:

i) study and analyse current practices, takt times and characteristics to identify challenges, methodologies and gaps within manufacturing processes

ii) develop a data acquisition method from manufacturing machineries for analytics using sensory inputs to accumulate characteristic heterogeneous data sets (e.g., a cutting machine to understand the behaviour and operational analysis)

iii) design and develop a cyber model that integrates machine characteristics, space and other control strategies

iv) analyse integrated real-time synchronous data management within cyber and physical models (proof of concept) in cloud

v) refine the acquired real-time data sets within cloud to define regression models (e.g., ML algorithms) to analyse the required parameters (e.g., takt time between the operations with isolation trees or KNN).

vi) develop and validate an integrated SM for textile manufacturing that is capable of real-time data analytics to reduce takt times, enhance decision-making.

## 1.4 Novelty of the Research

The main aim of this research was to integrate ML, CC and CPS technologies in a single platform in a manufacturing scenario. The integrated platform was called ‘SM’. The present research initially focused on the present challenges and limitations affecting manufacturing. This research also aimed to pinpoint the key factors of structured implementation of ML algorithms on a data set collected in the context of a complex operation in the manufacturing industry using the textile industry as a case study. Integrating the technology into real machines was challenging in a real-life scenario. Examples of complex operations in the textile industry include cutting, sewing, folding and packing, which must be underpinned with takt times. Takt times and system analysis contributed to the problem statements of the present research, giving a clear understanding of the flaws within the system and leading to a broad area of research, identifying the following important areas of research novelty:

i) Takt times in the manufacturing was addressed, as a reduction in takt time results in significantly increased productivity. Findings from these studies can be applied within similar manufacturing industries and serves as a benchmark. The efficiency gains

ii) Communication in manufacturing industries must be addressed because latency in communication between the operators, as well as operations, results in high levels of waste and reduces productivity. Such problems are often caused by poor decision-making and process analysis. In the present research, communication within the manufacturing industry was addressed via a cradle-to-cradle approach. This approach defines the processes of industry in a sequential and observed pattern to address the intense manufacturing that needed addressing. These decisions are often decided by the operation manager and department leads. Communication enhancements were made by implementing cloud communication to enable all operators and decision-makers to visualise and confirm decisions. This resulted in enhanced communication and better decision-making.

iii) Inventory management in intricate manufacturing industry often creates complications, making it difficult to maintain and retrieve. Observations revealed a high volume of inward and outward inventory due to uncertainty in production patterns and market expectations. These issues must be addressed to reduce inventory and emphasise the value of SM. Enhancements in reduced inward and outward inventory emphasises real-time manufacturing rather the traditional approach to manufacturing to aid in space optimisation, work order optimisation and stock management.

iv) Technology plays a major role in overcoming the challenges associated with traditional manufacturing and addressing the aforementioned challenges. Research was conducted on how to enhance decision-making and reduce takt times. These tasks were examined by analysing previously collected data to predict the future behaviour of operations and determine the machines used in the process. These predictions helped achieve better takt times while reducing lead times. The next manufacturing challenge involved enhancing communication. This was addressed by considering CC and transparency between the operations and operators. The present research helped operators understand the job profile they were assigned to, which enhanced the integration of operations by addressing the verticals of manufacturing in a cradle-to-cradle approach. Lastly, inventory management was addressed by analysing the solution in a virtual environment. AR/VR tools were used to address critical issues by visualising the manufacturing operations. The behaviours of the virtual components were subsequently analysed, along with real-time characters, which provided a sustainable result. The DT proposed includes these novel introductions from the research would help similar industries to address convoluted manufacturing practices. The DT proposed included i) DT proposals; ii) the implementation of DT principles, such as ML algorithms, CC and the integration of AR/VR technologies with a proof of concept and iii) future scope and conclusions of the research.

## 1.5 Thesis Organisation

Chapter 2: State of the art in the manufacturing industry

This chapter comprehensively describes current trends, challenges and related work in the field of manufacturing. Two surveys were conducted as part of this research to gauge existing market trends and technological standards. Further, a detailed methodology of ML algorithms and anomaly detection (AD) techniques are discussed.

Chapter 3: Manufacturing field study

This chapter describes the detailed methods adopted in the field study conducted on Australian manufacturer SleepCorp Pty. Ltd. SleepCorp is a mattress protector manufacturing company that uses complex manual operations. This was an ideal case study for exploring the SM framework because, if the efficacy of the framework could be demonstrated in this case study, this would suggest that other industries could also benefit from the framework with minimal changes to it.

Chapter 4: Smart manufacturing framework

This chapter outlines the novel SM framework. The framework is considered based on all possible machinery, software implementations, ML implementations and possible integration with ERP and MES. This framework was developed for a general manufacturing industry. To provide a proof of concept of SM, a case study of a mattress protector company was considered.

Chapter 5: Enhancing efficiency in manufacturing

This chapter illustrates the implementation strategy of the SM framework in a manufacturing scenario. The chapter first discusses the data generation and collection strategies before outlining the results and analysis.

Chapter 6: Cloud-centric digital smart manufacturing

This chapter consolidates the research outcomes of two major research problems: a decision-making framework and low-volume manufacturing. These research problems were addressed by integrating advanced technologies, such as CPS and CC. A cost and time analysis based on the earlier system compared with the new SM system is discussed in detail. Figure 2 depicts the thesis organisation.

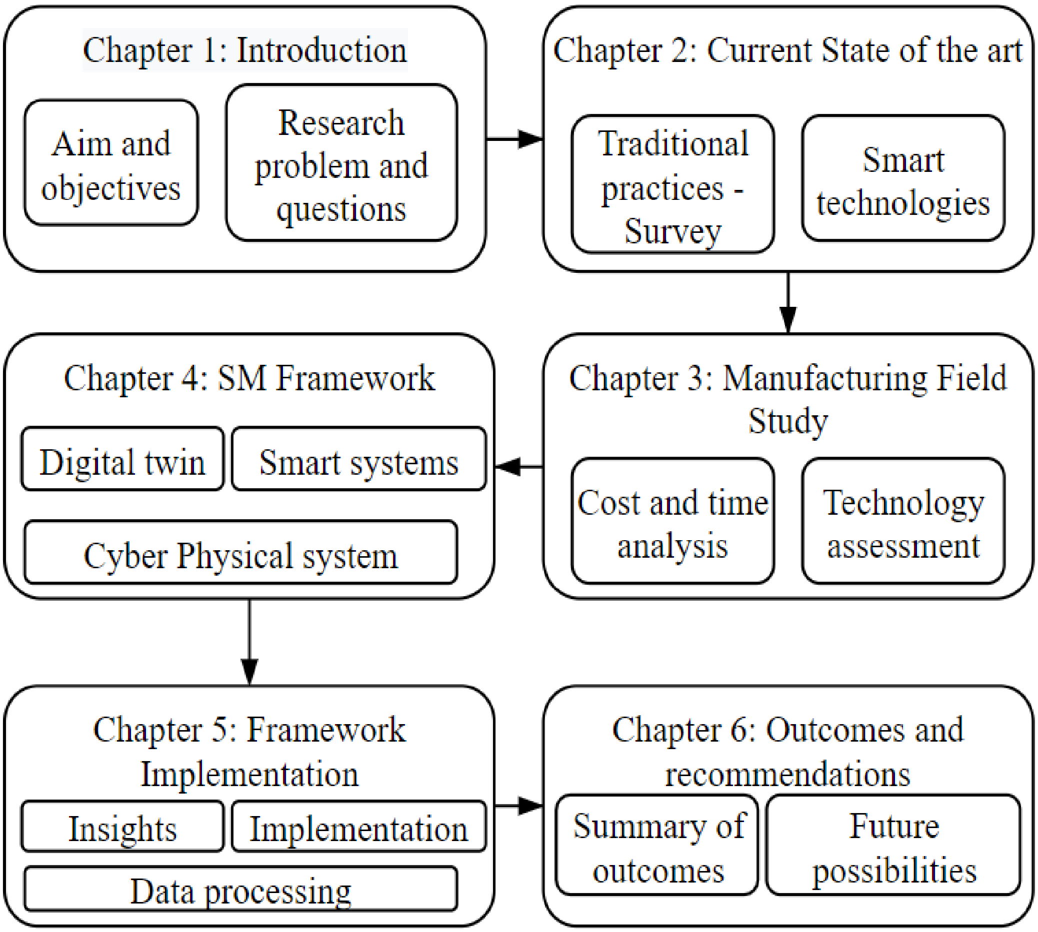


**Figure 2 Thesis organisation**

Chapter 7: Conclusions and recommendations

The thesis concludes by highlighting the main outcomes, summarising the analysis and outlining the future scope of the research. The future scope of the research includes a cost analysis of the implementation, a description of the security concerns of the CPS and an exploration of advancements in the implementation of ML and AD techniques on high-dimensional manufacturing data.

Chapter 8: Future scope

This chapter provides a clear overview of future directions for the research, including revisions of ML algorithms and improvements to the CPS system integration. Potential applications to manufacturing and other similar industries, such as the mining, transportation and medical industries, are discussed.

# 2 State of the Art in Manufacturing Industry

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This chapter describes the current trends, challenges and related work in the field of manufacturing. Two surveys were conducted to gauge existing market trends and technological standards. Further, a detailed methodology of ML algorithms and anomaly detection techniques are discussed.

This chapter is based on the following sources:

i) **Sourabh Dani**, Jiong Jin and Ambarish Kulkarni, 'Current state of art industry survey in Industry 4.0 manufacturing industries', submitted to the Journal of Industrial Engineering and Management, November 2021 (impact factor: 3.9).

ii) **Sourabh Dani**, Jiong Jin and Ambarish Kulkarni, 'Comprehensive survey of Real-time anomaly detection in High Dimensional Data in Manufacturing scenario', submitted to the IEEE International Conference on Cloud Computing, October 19–23, 2021.

## 2.1 Introduction

This chapter covers the challenges affecting traditional manufacturing practices, specifically the complex and convolute heterogeneous characteristics of the textile industry, which is used as a case study in the research. The chapter outlines the significance and exponential growth of industry 4.0 and relevant benefits for manufacturing industry. Further, a detailed literature review of SM and an outline of its important elements are provided. Cyber modelling, ML, CC and AR/VR are discussed to evaluate adaptable technologies that can address manufacturing challenges. Individualisation and the need to address the modern problems associated with manufacturing have arisen due to ever-evolving market needs and the influence of products on a global scale. There is an additional need to maintain competitiveness. Advancements in technologies, such as the invention of cyber systems, advanced physical machines, advanced data-driven technologies and solid integrated communication tools, offer means of overcoming traditional problems in the manufacturing sector. The integration of cyber and physical systems has gained major importance in recent decades across the manufacturing industry. This chapter discusses the following key points:

i) In the first section of LR, current manufacturing practices and the challenges affecting the manufacturing industry are discussed. Further, industry 4.0 standards, SM trends and related technologies for adoption to overcome challenges are outlined.

ii) A survey of the Australian manufacturing industry was conducted, and a related questionnaire is outlined. The related outcomes, questions and target audience are discussed in detail.

iii) Detailed literature on technologies, such as development of a framework using cyber and physical systems, is reviewed. Techniques, such as digitisation, 3D modelling, core-enabled systems and the capturing of CPS characteristics, are presented. Further, digitisation, engineering techniques, deployment methods and communication programming relating to the implementation of CPS are discussed.

iv) Cloud in the context of CPS is extensively discussed, covering current practices, deployment methods and varieties of implementations in an industrial context. Cloud service models for adoption are identified and described.

v) The application of ML in manufacturing based on the CPS and cloud integration models is discussed as a means of addressing current challenges. Literature on the limitations of applications of ML in manufacturing is explored, with potential solutions identified.

## 2.2 Traditional Manufacturing Practices and Gaps

Manufacturing plays an important role in a country's economy, comprising multiple levels of employment, cross-disciplinary industries and advanced machinery. This section explores existing methods of manufacturing, as well as associated challenges and techniques that have been used to overcome them.

### 2.2.1 Traditional Manufacturing Practices Survey

The manufacturing sector is an important part of a country's GDP. Manufacturing has many complex operations that it uses to deliver on the multi-disciplinary requirements of the market. Manufacturing industries are globally competitive, hence optimal process are necessary. The flow between operation and disciplines needed optimisation to enhance required productivity (e.g.: raw goods to finished products). Manufacturing generates more than $100 billion in the Australian economy and directly and indirectly employs more than 1.27 million people (Moustafa, Turnbull, & Choo, May 2019).

The survey conducted examined the challenges faced by Australian SMEs. The Australian manufacturing industry encompasses research and development, design, logistics, production, distribution, sales and services. The methodology of the survey focused on demographic questions. Initially, the survey was divided into regional and overseas manufacturing. The demographic questions related to participants' age, qualifications, current role, type of industry and number of employees in their organisation to understand the size of the industry. Further, participants' digital knowledge was assessed using the multiple grid questions to underpin the SM awareness. In addition, the implementation of integrated systems, such as ERP and MES, was surveyed. CC aspects of manufacturing were also outlined using cloud services, and cloud services implementation strategies were evaluated. Table 1 details information on the questions and expected outcomes.

**Table 1 Australian manufacturing survey**

| Topic | Description | Question | Outcome |
|---|---|---|---|
| **Details related to geography, age, qualifications, current role, industry type and experience.** | This section asked about participants' location of work, nature of the industry they were working in and their level of experience. | i) Where do you live currently? | If they were located outside Australia, the survey was terminated. If they were located within Australia, the next question appeared. |
| | | ii) Please select the state you are living in: | To identify where precisely the participants were located within Australia. |
| | | iii) Please select your age range. | To identify the target population. |
| | | iv) Please select your highest qualification. | To segregate participants according to their qualifications. |
| | | v) Please select the role you are currently working in. | To identify the nature of participants' roles. |
| | | vi) Please select the type of manufacturing industry you belong to: | To gather demographic information on the type of industry to divide the participants according to their industry. |
| | | vii) Approximately how many employees are working in your organisation? | To distinguish participants based on their industry, such as SMEs or large-scale industry. |
| | | viii) How many years of experience do you have in your field? | To establish participants' level of experience in their industry. |
| **Digital technologies awareness** | This section of the survey assessed participants' awareness of digital technologies within the manufacturing industry. Questions on a mid-management level and high- | ix) How much do you know about digital technologies? | To identify participants' ability to answer the remainder of the questions in the section and subsequent section while also helping to group participants based on their level of knowledge of digital technologies. |
| | | x) Please choose from the following digital technologies that you are aware of. | To gauge participants' knowledge on digital technologies such as ERP, RFID/Barcodes and cloud technology. |

| | | | |
|---|---|---|---|
| | management level were posed. | xi) Which of Enterprise Resource planning (ERP) services are highly useful? | If they ticked ERP in the previous section, this question asked about the services they might be using within their organisation such as for inventory management, market research analysis, accounts and finance and customer relationship management (CRM). |
| | | xii) Please choose the reasons form below for not using (multiple answers are allowed) | If they selected the ERP option, this question asked about the reason why they were not using ERP services. |
| | | xiii) Please choose the application of cloud services within your organisation. | To determine whether the participants were using cloud services, such as Google cloud services and office365. If they were using a cloud service, this implied that if there was a potential development with respect to a cloud manufacturing scenario. |
| | | xiv) Within next three years, which of the following 3 major improvements you want to implement through digital technologies? (Multiple answers are allowed) | To identify whether the organisation has considered any improvements, such as machine life predictions, line balancing, resource management and production planning, which directly affect the production rate within SMEs. |
| **Government assistance and professional help.** | This block is to understand whether the participants are aware about the government programs in upbringing the SME business and the professional help they might be interested in. | xv) Are you aware about the local, regional, national or government initiatives to support your business in your industrial transformation? | Government assistance packages are available for SMEs. This question verified whether participants were aware of these programs; if not, they could request more information on them. |
| | | xvi) Thank you for taking this survey. Please choose from the following professional services that you might be interested in. | Similar to the previous question, participants may have been aware of certain programs but lacking the professional needed to implement them. This question aimed to help the researchers map the businesses accurately. |

## 2.2.2 Operational Inefficiencies

More than 70% of survey participants said that manufacturing was vital to the Australian economy. Manufacturing today faces two distinct but unique challenges: global competitiveness and personalised products. Australian industries, specifically the textile industry, face high labour rates and inefficient traditional manufacturing practices. Australia has the highest labour rate of all other countries, as depicted in Figure 3. A high labour price was influencer for automation; this resulted in meeting global competitive demands. In addition, approximately 70% of the Australian manufacturing sector is attributable to SMEs (Geoff Gilfillan Statistics and Mapping Section, 2018). Technology adoption was seen as occurring at slow pace due to a lack of affordability stemming from increased set-up and maintenance costs (Caihong, Zengyuan, & Chang, 2019; Cheng, Liu, Qiang, & Liu, 2016).

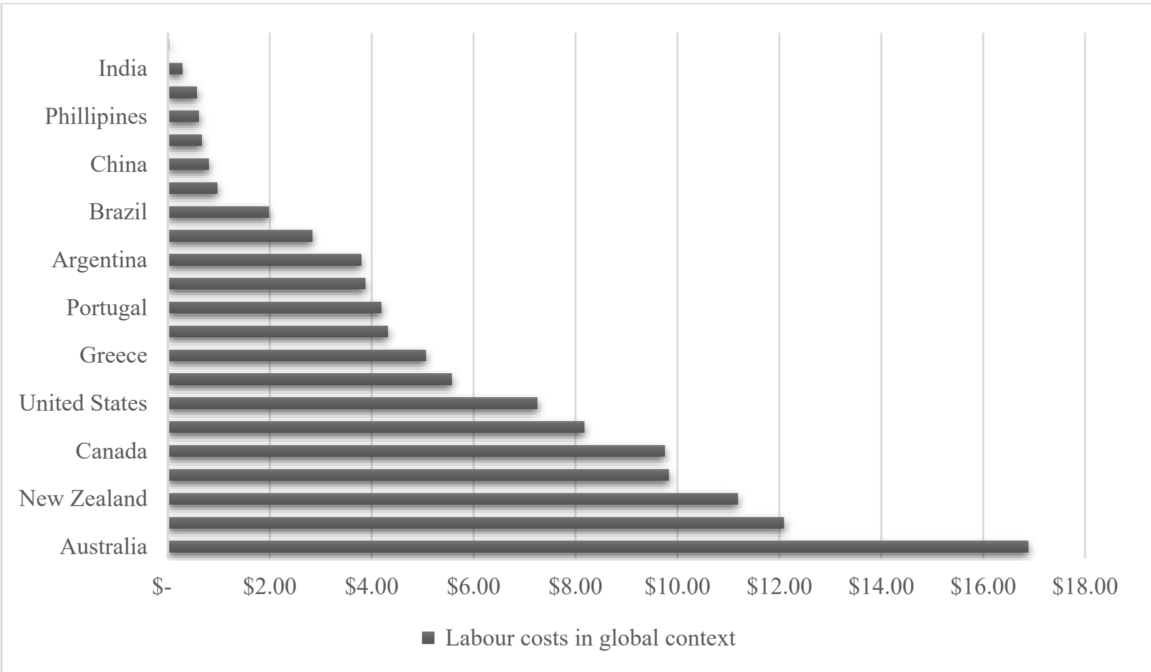


**Figure 3 Labour rates compared to global context**

Although the Australian textile manufacturing industry has boomed since the early 1970s, it mostly used traditional practices. The textile manufacturing industry, as depicted in Figure 3 (Australian Trade and Investment Commission, 2019), faces significant challenges compared with other industries due to its heterogeneous nature. Textile manufacturing consists of i) marketing and sales, ii) design and planning, iii) manufacturing and quality inspection and iv) inventory and delivery. Marketing and sales teams face significant challenges relating to customer expectations, personalisation, sales, product costs and value propositions (Ding, Zhang, Chan, Chan, & Wang, 2019; Dombrowski, Wagner, & Riechel, 2013; Fucheng & Guoliang, 2015; Gao, Li, & Chen, 2015). Among other expectations, design and planning was not limited but faced conceptual timelines, budget restraints, resource management, competitor benchmarking threats, decision errors and related warranty issues. Manufacturing and quality faced the following challenges: inefficiencies, skill and operational gaps, higher wages, inventory and supplier-led issues, maintenance issues, miscommunications, defects and rejections, and rejigging. Inventory and delivery departments often face challenges relating to product mismatch, miscommunications, personalisation, breakdowns, and overstocking issues.

Significant challenges faced by the textile industry include shorter product life cycles and an increased number of personalised variants. The requirement for individualised products based on customer demands is fulfilled using the same manufacturing processes. Therefore, the textile industry requires high inventories to fulfil its orders. Reliance on supplier raw materials and inventories of raw materials are also increased. As a result, the sector faces a lack of global cost competitiveness and waste-reduction strategies. This significantly affects costs due to the need for reworking and the rejigging of operations. Each manufacturing station is a single unit with complex and convoluted operations. High skill requirements and manual interventions are typical. Mere interconnection within manufacturing sub-systems increases costs and surpasses budgets.

More frequently, miscommunication and decision errors due to a lack of centric data are a challenge. Inadequate integration strategies stemming from traditional practices within sales, planning, design, manufacturing, purchase and supplier base result in last-minute, costly decisions. As manufacturing operation and related discipline’s function parallelly, control strategy was required for unproductive manual interventions. Hence, decision-making is not based on data-centric analysis. This inefficiency affects customer deadlines and, as a consequence, brands themselves. Current traditional practices are not set up for the cost-effective manufacture of personalised products, resulting in increased product delivery times to customers and reduced global competitiveness.

Recent trends and the emergence of hybrid manufacturing environments with real-time information exchange between the numerous operations have resulted in changes in practices. However, to date, these changes have been limited to single operations and have failed to capture all the heterogeneous characteristics of manufacturing. Examples include seamless real-time interfaces within marketing, sales, design, planning, manufacturing, quality, inventory and delivery. Further, increased environment awareness and related legislation have led to stricter practices for product disposal. Thus, textile manufacturing processes are a risk to global competitiveness due to versatile, intricate and inherently complicated systems, in addition to multiplying product variations in line with the trend of personalisation.

### 2.2.3 Decision Framework

Interdepartmental decision framework is vital in manufacturing scenarios. Decision framework was an important influencer within manufacturing and had economic impacts for an industry. More than 80% of the Australian manufacturing industry lacks an appropriate and validated decision framework. The financial success of an organisation depends on the important decisions made and execution of strategies. In manufacturing, planning and productions are interrelated, however overridden by complexities ever present (e.g.: decisions were instantaneous without scientific rigor, dependent on personal experiences). However, the present research showed that the lack of a decision-making framework leads to inefficient manufacturing. Making viable and economic decisions is important to the growth of the manufacturing industry. Money flow analyses, project management costs and projected costs related to engineering are directly proportional to the rational decisions taken beforehand.

Decisions made during manufacturing are also important. Different departments, such as sales, marketing, engineering, management, accounts, production and warehousing, must communicate regularly to avoid hidden costs. The product lifecycle and economical life cycle must be validated and neatly executed via a leak-proof implementation strategy. When making important decisions, management must understand the core analysis of the manufacturing. A core analysis can be conducted by implementing multiple analysis algorithms into a framework. Cost–benefit analyses and takt time analyses are two major strategies for evaluating the performance of a framework. The present research showed that a viable solution is more important than capable manufacturing. Critical decisions within manufacturing enhance the output compared with poor decision-based manufacturing. The problem of a decision framework arises within the production lifecycle indulged due to multidiscipline. Major decisions depend on sales volume, as well interdisciplinary communication protocols (e.g.: engineering and planning teams). In addition to quality assurance, warehousing end logistics play an important role in customer satisfaction. Further, sales and services enhance the performance of a product. The five phases of decision framework are planning, arrangement, management, relevance and execution. These five pillars must be as strong as possible to maintain a high producible manufacturing industry.

### 2.2.4 Low-Volume Manufacturing

The planning, management and execution of production must be tailored to low-volume manufacturing. Manufacturing industries often produce large volumes of quality products but fail to manage the raw materials and ready-to-deliver products. Since the advent of the manufacturing industry, every industry has sought to improvise its manufacturing strategies. Customisation or individualisation is important in the era of Industry 4.0. All customers have specific needs when it comes to buying personal products. Irrespective of the nature of the industry, customisation is needed to fulfil a particular objective. The characteristics of a product, market behaviours, expected sales, amount of marketing and quality of the product all affect the performance of the product in the market. To achieve strong performance, products must feel as though they are tailored to the individual.

Low-volume manufacturing is the major objective of every manufacturing industry. To approach low-volume manufacturing, all industries conduct research and development, and planning towards advanced manufacturing. Research has suggested that low-volume manufacturing can be achieved by number of ways, though a proven case study or a validated analysis has yet to be presented to date. Engineering low-volume manufacturing is highly uncertain. Considering all the parameters of the manufacturing industry may cause engineers to second guess their own analysis. While research has suggested that DT or a CPS can be applied to overcome traditional problems, analyses of implemented DT are lacking. Further, low-volume manufacturing must provide vital information of anytime anywhere.

Research conducted in the field of manufacturing has led to an understanding of the basic requirements of CPS. A simulated and validated strategy of low-volume manufacturing is needed for the manufacturing industry. Most low-volume manufacturing strategies pertain to specific industries. However, at present, a single framework or a strategy that can be applied to all other industries of similar nature is missing. OEEs and OEMs have their own strategies and, due to the nature of the industry, need not be concerned with stock and raw materials.

## 2.3 Smart Manufacturing

The first of the three major revolutions that have transformed industries from conventional methods to advanced methods was the first industrial revolution, which introduced commercial steam and machinery in the 1700s. This was followed by the. second industrial revolution, which applied electricity to machinery, leading to mass production in the late-twentieth century. The third industrial revolution initiated full length usage of computers at the time of the Second World War. The most recent industrial revolution is the fourth industrial revolution or 'Industry 4.0', as coined in 2011 by Henning Kagermann, chief of the German National Academy of Science and Technology. The Industry 4.0 movement was initiated by strong technological contenders, such as BASF, Deutsche Telecom, Bosch, Daimler and others in Germany. Industry 4.0 gained in momentum in other parts of the world, such as in Japan, the UK, China and the US. Industry 4.0 is gaining importance across the globe in several industrial sectors. Figure 4 depicts the adaption to Industry 4.0 by industrial sectors worldwide.

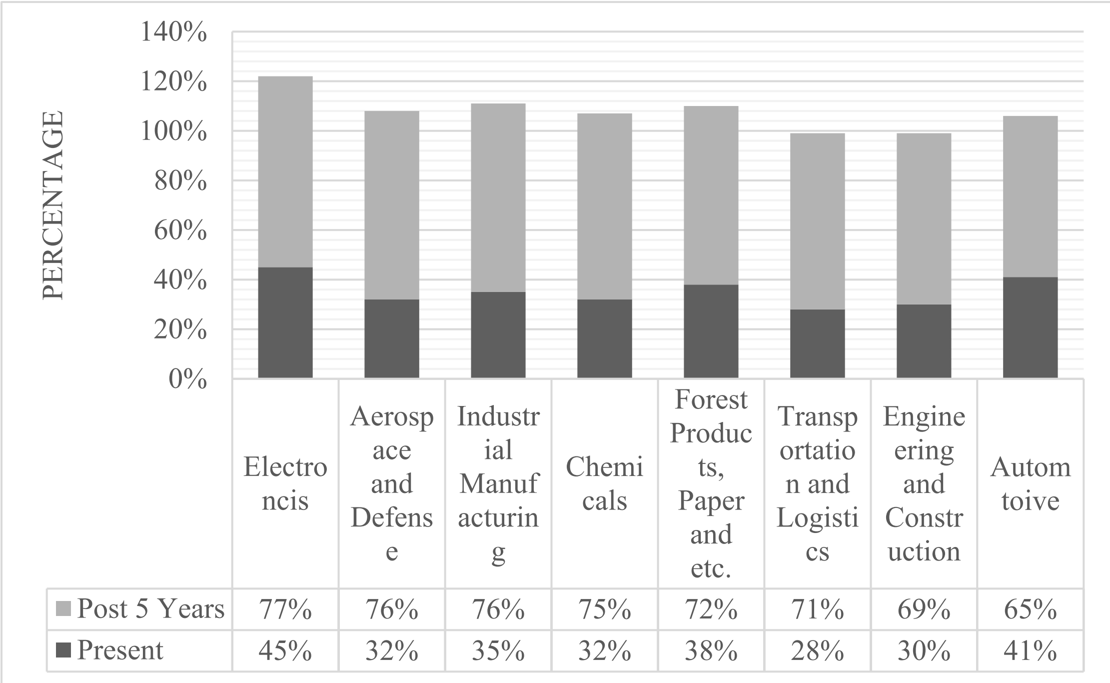


**Figure 4 Adaption of Industry 4.0 in various sectors from 2016 till 2020**

Industry 4.0 has played a critical role in the integration by industrial anchors, such as GE and Siemens. In recent years, Industry 4.0 has enhanced manufacturing efficiency by harnessing advanced technologies, such as CC, DT, cloud networked robotics (CNR), artificial intelligence (AI), regression analysis (RA), task analysis (TA), predictive models (PM) and ML algorithms. Industry 4.0 manufacturing processes autonomously exchange information and trigger actions by controlling machinery connected by advanced technologies (Iarovyi, Mohammed, Lobov, Ferrer, & Lastra, 2016; Ivezic & Ljubicic, 2016). This innovation has improved manufacturing and engineering processes, material usage and the supply chain, as well as the life cycle management of industrial operations. In addition, recent advancements in cutting-edge ICT technologies have led to the introduction of real-time applications for industrial manufacturing (Zhou; Zhu, Li, & Wu, 2018). These applications entail more precise design and rigid frameworks for successful implementation, thus automating processes. In the context of Industry 4.0, there has been a need to achieve a systematic manufacturing process by maintaining efficiency and providing an economically competitive solution. Therefore, there is a need for a new paradigm (i.e., SM) to be established as the hallmark of the fourth industrial revolution.

To date, Industry 4.0 has represented manufacturing systems, including material flow and a simulation model, as CPS for augmented production and planning strategies (Vachálek et al., 2017). Establishing manufacturing as CPS required smart operational interconnection, interaction with control and management converging both spaces (Fei Tao & Zhang, 2017). Further, challenges such as interconnecting heterogeneous physical systems and integrating these bi-directionally to cyber system have been highlighted. This chapter presents the adoption of an SM inheriting CPS to enable seamless real-time integration from product design to delivery to advance value chain traceability and enhance efficiency (Ferrer et al., 2018). (Qu, Jian, Chu, Wang, & Tan, 2014) argued that the idea of embracing SM in a full-scale manufacturing plant is impractical and further suggested a lack of practical implementation due to complex and convoluted manufacturing characteristics. (Wang, Wan, Zhang, Li, & Zhang, 2016) presented a smart factory based on a cloud coordinator for machines, conveyors and products for distributed self-decision and intelligent mechanisms. Using an Industry 4.0 approach, (Subakti & Jiang, 2018) proposed mobility aspects, arguing for the use of mobile deployment for interacting displays. Meanwhile, (Sezer, Romero, Guedea, Macchi, & Emmanouilidis, 2018) argued that an enhanced comprehension of complexity overwhelmed manufacturing information through mobile deployments compared with static displays. Industry 4.0 has enabled low-cost data acquisition and conditioning monitoring for lathe operations and predictive maintenance (PM) activities. A novel integrated SM modelled is detailed in the following sections to address these challenges and establish efficacy for enhanced productivity and decision-making.

### 2.3.1 Industry 4.0

The industrial and information technology industry has undergone considerable change. As the industry entered the Industry 4.0 era, it progressed from embedded systems to the cyber–physical world. Manufacturing is now possible via the Internet, which has paved the way for intelligent direction by achieving internal and external network integration. The development of Industry 4.0 was studied in this thesis. Cyber–physical systems were introduced in Wise Information Technology 120. This subsequently led to the application of Industry 4.0 in intelligent manufacturing. The present research analyses the future of Industry 4.0 and intelligent manufacturing Cheng et al., 2016).

CPS and cloud manufacturing were involved in achieving Industry 4.0, which was set to be a new manufacturing objective. While Industry 4.0 was revolutionary, it was not without defects, though it aimed to achieve nearly zero defects. In this research, the possibility of a platform that denotes the advanced manufacturing of cloud things was explored. This proposal not only aims to achieve the objectives of Industry 4.0 but also accomplish the goal of zero defects by applying automatic virtual metrology technology. Combining Industry 4.0 and AVM to achieve zero defects led to the beginning of the era of Industry 4.1 (Cheng et al., 2016).

Cyber–physical additive manufacturing systems consist of the tight integration of cyber and physical domains. This union, however, induces new cross-domain vulnerabilities that pose unique security challenges. One such challenge involves preventing confidentiality breaches caused by physical-to-cyber domain attacks. In this type of attack, attackers use side channels (e.g., acoustics, power, electromagnetic emissions) in the physical domain to estimate and steal cyber-domain data (e.g., G/M-codes). As these emissions depend on the physical structure of the system, one way of minimising information leakage is to modify the physical domain. However, this process can be costly due to added hardware modifications. Instead, (Chhetri, Faezi, & Faruque, 2016) proposed a novel methodology that made cyber-domain tools aware of existing information leakages. The authors then proposed changing either the machine process or the product design parameters in the cyber-domain to minimise information leakage. This research methodology aids the existing cyber-domain and physical domain security solution using the cross-domain relationship. The present research aimed to implement the methodology in a fused-deposition model based on a Cartesian additive manufacturing system. The methodology achieved a reduction in mutual information of 24.94% in the acoustic side channel, 32.91% in the power side channel, 32.29% in the magnetic side channel and 55.65% in the vibration side channel. As a case study, to help understand the implication of mutual information drop, and the calculation of the success rate and reconstruction of the 3D object based on an attack model are presented. For the given attack model, this leakage-aware CAM tool decreased the attacker success rate by 8.74% and obstructed the reconstruction of finer geometry details (Chhetri et al., 2018).

In this research, recent developments and applications of CPS in the manufacturing industry were studied. The literature contains some models of system design and system development for Industry 4.0, but few examples were found specifically for manufacturing systems modelling and simulation. The present work proposed a novel system framework of integrated cyber–physical simulation modelling environment for manufacturing 4.0. This framework incorporated an architecture integrating an aggregate cyber space controller (ACSC) with a physical space distributed controller (PSDC). The concepts of DT, distributed artificial intelligence, CC and distributed autonomous control were deployed in the framework with the aim of exploring the future potential applications of systems modelling and simulation for manufacturing Industry 4.0 systems. The framework proposed has an extension of CPS and provides a scenario of hybrid cyber space simulation and a physical space discrete controller for manufacturing 4.0 (Lin, Low, Chong, & Teo, 2018).

Additive manufacturing (AM) uses CPS, which is susceptible to cyber-attacks. By these cyber-attacks there will be physical damage to manufacturing systems. In CPS, scientists have modelled various attack-detection methods for detecting attacks on the integrity of a system. However, attack detection is in its infancy in relation to AM. Moreover, analogue emissions (e.g.: electromagnetic emissions, acoustics) from the side channels of AM have not been fully considered as a parameter for attack detection. To address the security issues surrounding AM, this research presents a novel attack-detection method that can detect zero-day kinetic cyber-attacks on AM by identifying anomalous analogue emissions that arise as an outcome of an attack. This is achieved by statistically estimating the functions that map the relationship between analogue emissions and the corresponding cyber domain data (such as G-code) to model the behaviour of the system. This method was tested for its ability to detect potential zero-day kinetic cyber-attacks in fused deposition modelling-based AM. These attacks can change various parameters of the 3D object, such as the speed, dimension and movement axis. The accuracy, which is defined as the ability of the method to detect the range of variations introduced into the parameters by kinetic cyber-attacks, was 77.45% (Chhetri, Canedo, & Faruque, 2016).

A number of initiatives have aimed to promote digital manufacturing (i.e., the adoption of pervasive, fine-grained CPS and of data-driven optimisation techniques within the manufacturing domain). These initiatives aim to increase efficiency during the running of conventional operations and allow for new production and business models, such as mass customisation or networked value chains. This research is planned in two phases, initially enhancing current operations efficiency and there after implement system overhaul. First, the present work elaborates on the often-neglected line-level automation and the importance of making it a priority in digital manufacturing, particularly when transitioning existing manufacturing to modern facilities. Next, this work describes the approach and references the specific technologies used for production deployment on the factory floor . Following this, positioning is introduced within a second stack jointly prototyped with partner organisations of reasoning algorithms. As entry points for added autonomy into manufacturing systems, they pave the way for automatic (re)configuration from high-level goals, as well as for error recovery. The present work provides an insight into the design of the next generation of software architecture for manufacturing and aims to contribute to the transition from early reference architectural models to design blueprints for actual technology stacks (Lüdtke, Delval, Hechtbauer, & Bordignon, 2019) (Novak, Kadera, & Wimmer, 2017).

## 2.4 Smart Technologies

This section details the smart technologies that have been used for more than a decade using singularly repeatedly in multiple industries, including how they are mainly used, the challenges associated with their use and proposed solutions.

### 2.4.1 Cyber Physical Systems

According to recent research, a key element of DT involves digitising the environmental modelling. Cyber modelling of physical entities uses point cloud data, which is a cluster of interconnected computerised data based on Cartesian origins. This system is integrated for network topology, service managers and data storage capabilities (Liu, Liu, & Sun, 2011).

Individualisation and the need to address the modern problems of manufacturing have arisen due to ever-changing market needs and the influence of products on a global scale. Further, maintaining competitiveness has become increasingly important. Advancements in technologies, such as cyber systems, advanced physical machines, advanced data-driven technologies and solid integrated communication tools, present new ways of overcoming the traditional problems faced by the manufacturing sector. The integration of CPS has gained major importance in recent decades across the manufacturing industry.

Research has suggested that CPS will be affected by evolved integrated solutions in manufacturing production lines. Mechanical and electronic items on the shopfloor will be prone to cyber models in achieving CPS, with additional advancing communication practices that enable the study of the behaviour of mechatronics. Such research would illuminate the behaviours of production systems by simulating manufacturing lines in CPS. Thus, integrated CPS systems could help in realising the vertical technologies and horizontal procedures of production lines.

Strong competition in the global market has led to flexible and reconfigurable production systems that can rapidly react to both endogenous and exogenous drivers. With this fast progression, a new production system model must be defined. The system should combine the KBFs and relevant KPIs to control the system to allow the right decisions to be made while using the simulation ICT tools. The model must be used in a cyber–physical system for the simulation ICT tools to be supported in making the right decisions and properly supporting the different functions.

This project aimed to develop an innovative manufacturing system based on a new concept that implemented methodologies, strategies and methods to transform the existing production systems to ones based on CPS technology. The present research compared the relevant KPIs with their KBFs. This research methodology has used in the industry to gather important information on constraints and opportunities for improvement in other contexts and has been validated (Boschi et al., 2017).

SM systems have been shaped significantly by CPS. Computation and physical processes are integrated in CPS. CPS can be used to represent the behaviours of both the cyber and physical parts of a system. Major vendors of manufacturing industries have conducted a detailed technical review of existing engineering tools and practices, presenting an overview of CPS technologies, components and relevant standards. Subsequent research has developed potential ways to enhance the tools, functionalities and capabilities that support the CPS development process (Jbair, Ahmad, Ahmad, & Harrison, 2018).

Various methods have been used to develop cyber models repressing physical entities mainly 3D modelling, laser scanning, ladder scanning, infrared scanning and photogrammetric procedures (Lin et al., 2018). Significant challenges arose during the development of cyber models. Among various challenges, digitising complex, and organic shapes of physical machineries with required textures (e.g.: reflective surfaces) are significant. Cyber models have been created manually, algorithmically (through procedural modelling), by scanning and via the triangulation of photographs. Recently, Quadra capture-based photo triangulation has been successful in creating coloured texture at higher model accuracies (Liu, Zhao, Tao, Zhao, & Li, 2018). An example of a warehouse digitised using photogrammetry is depicted in Figure 5. Major machining data have been collected from digital data engendered from adapted computer-aided models (Nguyen, Leu, & Liu, 2017). These verticals of manufacturing must be integrated and visualised using cyber models to prevent them from becoming digital islands. LR suggests that developing cyber models of the physical shopfloor can affect the visual commissioning of the processes.

**Figure 5 Photogrammetric warehouse model**

Most machining information produced by CAM-CAD software is in the form of digital data. Using this approach in traditional manufacturing systems may be misleading if both software and hardware systems are not suitably allied. This can bring about a need for reworking due to the errors produced and risks involved in practising a deluded system in the manufacturing industry. (Kao et al. 2018) described an intelligent system under manufacturing termed an innovative manufacturing system (I-MS) by combining process and task management, system tools and production knowledge to create a cyber-system that demonstrated networking and system architecture. The authors showed that most of the time taken for the production and workload of the machinery could be reduced. This approach has been successful due to the interference of networking with machinery and helps I-MS as a system to be used for further studies in manufacturing arena. (Liu, Zhao, et al., 2018) described the physical architecture of an I-MS and thorough design of a digital system, innovative logistics, control system and workload management. The network interface, connections, machine logistics, machine tools, interactive components, RFID, sensors, real-time gears in a system, monitoring of processes, processing of units and digital data connected to the Internet build collaborative systems interacting with one another. Further, producing more of such systems helps in measuring the quality, performance, efficiency and management of electrical machinery, water, plants, and environmental areas, which promotes automation. The following section describes the different norms and regulations affecting the integration of CPS.

#### 2.4.1.1 Exploitation of Current Tools and Norms

The major tools that aid in the design of 3D models are retailer specific, and most are software environment controlled. These tools ensure a good stabilised, vigorous operational system that supports multi-functional and point-solution architecture with very low agility. Research has described many methods and techniques for using technical data to achieve the CPS. Nevertheless, these approaches often address a particular set of rules and only partially satisfy the overall architecture of Industry 4.0. A cradle approach in CPS, such as engineering, automation, integration and the implementation of several methods, is of major interest. For communication within CPS, often OPC-UA communication is used to extract the data from information layer which is associated with electronic devices and designed 3D models.

#### 2.4.1.2 Model and Module-based Systems

Architectural frameworks and different modelling languages have been defined by various researchers. Multiple approaches have been taken to many SysML designated for content creation. Anecdotally in theory hardware (e.g.: mechatronic part) and software are integrated seamlessly to provide required output. The complexities of the manufacturing system required several integrations of hardware and software found missing at this point in time (Luder et al. 2016). This approach was first implemented by software called the Siemens SIMATIC Automation designer, which featured the instantiation of model parameters in accordance with the library of a particular mechatronic model. Comprised of a module and a model-derived design flow, the designated system was comprised of component models that were driven by architectural specifications. This was created through a reference architecture, which was further defined with the scope of the work, composition of the module and content. The development, structure, operation and integration were contributed by the framework of the referenced model. Interdependencies within various operations for manufacturing product has potential to be eliminated with novel industry 4.0 method. The approach is also termed 'logically nestable modules' part of industry 4.0 method.

Prototype-based models have a demonstrated track record and have been embraced in the fields of engineering, business and production. A series of methodologies have been applied to prototype-based models development varying from detailed independent system approaches to system-dependent methods. A module-based approach was from various fields to enhance the efficiency and tractability of the development process. In the field of manufacturing, the design of an automation distributed system proposal has been formulated. In the module-based method, a key aim is to facilitate an advanced level of design actions, such as the adoption of module- and prototype-based model designs, to lay a groundwork for establishing demarcated interfaces amid deployment and design across all development phases. The demand for module-based approach may be high due to design knowledge salvage captured by the module components used. Manufacturing systems are comprised of numerous components of varying complexity and scale, from single sensors to complex system modules. A new way of integrating these components, which are logically designed to evolve, is an automation system that implements, tests and validates. Many such logical systems of automation can be assembled with larger physical control systems or can reside separately on embedded network systems. These devices form the CPS with a network interface and interact with one another, together forming a whole device system.

#### 2.4.1.3 Module Programming and Implementation

Components of deployable CPS can be designed in a variety of forms. The manufacturing of disseminated embedded devices entails the functioning of every unit in the distributed system. A composition of interconnected components, such as functioning units or port-based modules mapped onto devices, form a distributed system. (Fay et al. 2009) argued that a distributed system nodule (i.e., distributed devices) may have distinct functions. The nodules provide the freedom to either use predefined prototype functions—functions that have set parameters and once the program control comes to a predefined prototype. A particular outcome is expected, as the parameters are pre-set, or there may be the unrestricted programming of control system applications based on the IEC 61131 standard for programmable controllers. Such automation system designs have been used extensively in the manufacturing industry to intertwine and sequence behavioural execution and adopt state-based patterns or designs, including the IEC standard for programming. In this system, a group of components is confined to a physical nodule, and a state-based component-level design technique is used. Module functionality can be defined using transition state illustrations for components and module behaviours and the definition of a transition from one state to another. This assures a simple system design flow and provides an option to distribute control programs throughout the hardware, including a network interface that connects distributed devices.

#### 2.4.1.4 Engineering Practices and Communication

CPS comprises widely networked design structures, including large numbers of human resources, information technology systems and automation modules. Communication systems in the manufacturing industry, commonly termed industrial communication design systems (e.g., Ethernet), can establish a connection between the distributed modules in a distributed system. Every component in the distributed module of the distributed system can communicate with another module in the distributed device. This provides a robust perpendicular and parallel integration in the interior of the automation design distributed systems. To explore this form of network automation system design, the present research investigated the efficiently of the connection. Seamless communication between computers and machines is vital. With globalisation, the use of web and internet to interconnect the computers to machineries to manage the collaborative manufacturing is gaining exponential growth. However, there are potential critical security risks or threats due to the use of web technologies, networks, the Internet, and other technologies in the field of machining that was beyond this formulation.

#### 2.4.1.5 CPS Simulations

Considering multi-disciplinary fields such as process control design, electrical project, mechanical design engineering, human-computer interaction (HCI), and other engineering practices was problematic. Further adding to this, there were still a number of loopholes in the steady use of data during all the life cycle stages. Although the idea of SM system goes unstated where the steadiness between virtual and physical illustrations would be achieved in every life cycle stage. Researchers around the world state that the walls restricting the realisation of current integration-solutions refers to mutually distinct prerequisites of the manufacturing fields involved.

#### 2.4.1.6 Mixed Reality

This section outlines the significance of mixed reality (MR) in enhancing the efficiency of manufacturing systems. There is a need for a higher order of accuracy and response, as well as interface design—all of which are critical elements in the manufacturing paradigm Cheng et al., 2016). Textile industry operations are variegated, and a seamless process flow in between the processes is needed (Lin et al., 2018; Nguyen et al., 2017). Traditional manufacturing systems inherited miscommunication and non-transparencies in operations due to a lack of real-time data (Ding et al., 2019; Fan & Chang, 2018). XR methods represent cyber models with a realism effect using AR/VR tools integrated in a cloud-centric platform enabled with ML algorithms. To overcome operational barriers in the textile industry, XR allows for the seamless integration of processes in a simulated environment that represents physical machinery (Lei et al., 2018).

While automated manufacturing processes are already widely used, AR/VR provides significant benefits and has experienced exponential growth in recent times. VR creates as an artificial simulated environment that provides a real-word experience, while AR overlays rendered experiences and data onto real-life environments and, therefore, enhances the perception of reality (Herwan, Kano, Oleg, Sawada, & Kasashima, 2018). AR/VR integrates part of XR simulated for real-time visualisation and improved operations before physical implementation. These methods ensure that activities such as design, planning and machining are conducted accurately and efficiently in the first attempt, without the need for subsequent rework and rejigging. In fact, the dynamic interaction of existing AR/VR applications, enabled by the sharing of information with the real working environment, has the potential to capture heterogeneous characters of convoluted manufacturing processes (Sezer et al., 2018; Stock, Schel, & Bauernhansl, 2019). A key challenge involves designing and implementing an integrated AR/VR manufacturing system connected to a cloud-centric platform (Krishnamurthy & Cecil, 2018).

A key goal is to interconnect seamless communication with operational machineries (e.g., automated services in manufacturing provided by service robots) to create manufacturing efficiencies, such as shorter head time, reduced costs and improved quality standards. The eventual goal of integrated platforms with automated manufacturing is SM that is as good as a real-world application, if not better and more efficient. In addition, SM introduces the concept of a virtual factory that captures information about the status and behaviours in a real manufacturing system (Ferrer et al., 2018). SM presents an integrated computer-based model regressing to physical and logical schema of real-world manufacturing. These technologies provide the following benefits: i) an immersive experience which provides the user with a sense of realism, presence and engagement; ii) interactivity inputs, encompassing user sensory controls, to guide the system's behaviour and allow for interaction for enhanced engagement in a real-world environment; and iii) multisensory immersion by connecting with human sensory systems (however, this is still in the conceptual stage).

## 2.4.2 Cloud Computing

CC platforms offer the on-demand delivery of computer power, database management, storage and other resources that can be accessed via the Internet. This form of access to applications and storage allows for real-time synchronisation, versatility and efficiency, which was not previously available (Monostori, Markus, Van Brussel, & Westkämpfer, 1996). It allows for seamless large data set storage and the ability to visualise and manage the data. Research has indicated that by 2025, almost 90% of the global market will use CC platforms (Bahrami, 2015). Hence, future proofing is required to instigate cloud architecture to reduce the use of local servers and minimise hardware and related maintenance requirements.

CC is an important invention that has facilitated the integration of various technologies, such as IoT, DT and ML (Hang, 2016; Romeo, Paolanti, Bocchini, Loncarski, & Frontoni, 2018). However, CC is limited by latency issues when used in context of IoT. Manufacturing systems require large data set transfers between machinery to sensors via the cloud, which results in computing inefficiencies. Real-time computing for machinery requires low latency, high reliability computational methods. One solution to the latency barrier is use of fog computing. Fog computing covers a discrete area of manufacturing and reduces latency in communication from sensors to the cloud (Li, Ota, & Dong, 2018). However, introducing another technology adds complexity to system, resulting in unpredicted errors from the system management. Sensory data connected to the cloud by surpassing data transmitters or propagators is another solution. Connecting data to the edge of the cloud decreases latency, which results in highly reliability SM (Lin & Lu, 2011; Linthicum, 2017). Once the sensory data has been collected, the data must be processed. Validating these data in real-time is complex and time consuming. The data processing uses fog or cloud edge solutions. Following this, resource allocation is conducted through the management system to process the data. Often, a lack of resource optimisation results in data ambiguity with unforeseen errors. To overcome issues of resource optimisation, the cloud-centric virtual shopfloor can be pilot tested (Maenhaut, Moens, Volckaert, Ongenae, & Turck, 2017). Resource management in the cloud results in unforeseen errors with a high data demand in a small amount of time. To overcome these errors in CC, novel algorithms must be fine-tuned or rewritten based on previous data sets (Rauscher & Acharya, 2014).

SM has a unique behaviour of demanding service-oriented networked manufacturing. This approach optimises and composes several complex operations to yield dynamic operations of the shopfloor. Here, several frameworks have been proposed. These frameworks often integrate CPS, along with other major technologies, such as communication protocols between online (cloud) to offline services (physical machine). Although advanced manufacturing has been proposed in various forms, the practical implementation is limited. It constitutes a formulated and structure component manufacturing with complex operations. However, it lacks clear and succinct elaborated practical implementation techniques (W. Liu et al., 2011). Along with SM, major technological verticals, such as the 3D printing of cyber models, have gained increasing interest in recent years in terms of industrial advances, design, manufacture and research. Researchers have proposed how SM can be supported for national growth in terms of the economy, and future developments have been highlighted with in-house manufacturing (Jawad, Bezbradica, Crane, & Alijel, 2019). Innovations in manufacturing along the industry 4.0 standards have gained importance in recent times with the integration of CMfg and IoT to overcome conventional structure of the modern shopfloor. Researchers in Korea proposed an assessment tool for SM that equipped along with current manufacturing practices to understand the behaviours, characters and future aspects of the organisation. Comprehensive and intuitional criteria for measuring readiness along the smartness of the shop floor have been identified. These types of assessment tools can assist medium-sized enterprises and small-scale enterprises to emphasise Industry 4.0 approaches (Sheen & Yang, 2018).

To resolve these issues, the industrial internet of things (IIOT) hub was proposed; it offered customisation and programmed connection between heterogenous operations and services, which were encapsulated and differentiated from individual behaviours (Tao, Cheng, & Qi, 2018). Addressing these heterogenous properties has expanded their major competition across significantly characteristically differentiated manufacturing industries. Global competition across industries has caused organisations to shift their concentration to automation and implement advanced manufacturing technologies in the production line. The main goals of implementing these technologies have been internal growth, operation optimisation and manufacturing efficiency (Lee et al., 2018).

To align with development, design, implementation, management and computation, there is a need to register the concepts and operations onto the cloud to structure them systematically (Bai, Fang, Tang, & Wu, 2019). A challenging task of CC has been to manage services, such as pluggable inputs and outputs and plug and play services. These services have helped realise smart factories enabled by the cloud. Several frameworks for cloud-based intelligent services, such as edge computing, CC, and REST based web services, have been proposed. One such framework constitutes dual RESTful based services to enable a pluggable application module (PAM). Production management in manufacturing processes is handled remotely on an intelligent platform supported from PAMs to target individual services. This type of framework has been tested for the fast and reliable deployment of SM using cloud services. Further, PAMs can also be used to facilitate PM (Fan & Chang, 2018; Liu, Hung, et al., 2018).

### 2.4.3 Self-Learning Algorithms

Artificial intelligence is an important paradigm in manufacturing achieved through algorithms. Amongst various algorithms ML provides a vast benefit including decision matrix within manufacturing. Major divergence between SM and traditional practices was a limitation that arose in previous practice caused by the adoption of technological advancements, such as ML, AI and IIoT. ML interfaced with deep learning enhances iterative decision-making to address the challenges of inefficiency in textile manufacturing. Previous research conducted on ML highlighted these as self-sustained fast efficient systems, minimising interruptions and reducing resource consumptions (Al-Gumaei et al., 2019).

Modern smart factories are comprised of IoT-based machines with inter communications and data transfer facilities for computations. IoT machinery further captures heterogeneous characteristic nodes within operations to develop optimal solutions using ML algorithms. Problems within operations are detected to allow for corrective actions to enhance system efficiencies. Previous studies on the applied context of using ML algorithms in manufacturing were limited to performance-based approaches. However, in a real-world environment, manufacturing can vary according to complex circumstances. Finetuning variances is a drawback of performance-based approaches. Changing to data-centric with ML algorithms to address manufacturing variances was proposed as an alternative approach. This approach adopted variances with the scope to output optimal solutions based on a data-centric knowledge base. This enabled varying heterogeneous characteristics in the manufacturing to be captured to enhance efficiencies (Huang, Lin, Chen, & Sze, 2018).

The textile industry has been subject to demands for low volume and high variation within personalised products. A robust integrated real-time data-centric platform was required to meet these challenges. Data inaccessibility results in inefficient computations and, as a consequence, a lack of optimal decision-making within manufacturing (Lenz, Barak, Mührwald, Leicht, & Lenz, 2013). To reduce takt time and improve efficiencies, cyber models have been simulated in the context of physical systems. These simulated cyber models are real-time interfaced with data computation using various ML algorithm. Cyber models have the properties of real-world machinery and allow for bidirectional associative inputs. They have the advantage of ensuring the logical flow of manufacturing processes using computed using ML technologies in a cloud-centric platform (Amanatullah, Lim, Ipung, & Juliandri, 2013). Implementing ML algorithms using CC technologies integrated with virtually simulated data can overcome major hurdles in the manufacturing paradigm. ML algorithms result in optimal decision-making and enhance efficiency in manufacturing (Jaensch, Csiszar, Scheifele, & Verl, 2018). Further, interlinked to testing on same technologies that improves product quality.

Data-centric ML models carry data leak risks. Hence, data integration requires strong concealed cyber security. Cyber security in real-time manufacturing poses barriers (e.g., uncertainty for deciding in investigating malicious threats) (Feng, Wu, & Liu, 2017). The issue of data leaks has been addressed using multi node algorithms. Real-time data computation for manufacturing control systems also requires high performance system reliability. This challenge had been overcome using software-driven artificial intelligence paradigms programmed in the cloud to enhance the high response in data computation in relation to hardware driven execution times (Chen & Bastani, 1991; Yao, Zhou, Zhang, & Boër, 2017).

#### 2.4.3.1 Machine Learning Algorithms

Manufacturing systems are complex and can be chaotic. An efficient way of approaching current demands for high-quality products is to use all the available essential techniques. CC is a promising new technology. Developments in ML offer versatility in manufacturing and can address challenges that arise within data sets. Inherently, ML has vast applications and related limitations (e.g.: model behaviour or accuracy) (Monostori et al., 1996). This research enhanced available techniques and structured complex data sets in a usable way for successful applications in complex environments such as manufacturing.

ML has made significant progress in the last decade. The field has become a major technological hotspot due to ever-emerging challenges and possibilities. Progress towards computerising or answering the human reasonings for unresolved questions in data are the main reason for this growth. Data representation is more symbolic than conceptual ( Monostori, 2003). The progress of ML towards a symbolic approach is based on cognitive reasoning and was hypothetical. Moreover, these can be modelled by acquiring, manipulating, associating and modifying data towards symbolic representation. Earlier systems that are known for their reliable knowledge of the establishment of intelligent systems attempted to overcome man-made computer systems. Unfortunately, representation in these kinds of approaches was in the form of rules and regulations. While these methods were proven effective, none was practical.

The field of ML is solely related to data. The data collected can be raw, processed, structured and even categorical. ML aims to overcome issues and solve problems. The data collected by machines is always unstructured. To define the types of data, the core of data science must be explored. DS can be divided primarily into two major verticals. One explains or explores past data, and the other makes predictions from the same data set. Past data are checked and verified to study the behaviour of the data. Data can be considered in two ways: univariate analysis and bivariate analysis.

##### 2.4.3.1.1 Data Expedition and Characterisation

Univariate data analysis explores the collected attributes individually. Data can be either numerical or categorical. Every type of attribute can be verified by visualisation. In analysing data, transformation is required. As such, categorical data can be transformed into numerical data by the process of discretisation. The process of data transformation from categorical to numerical data is called encoding.

As mentioned earlier, univariate is further divided into two major verticals: categorical and numerical. Categorical data are data collected in a format other than numbers. Therefore, there are fewer possibilities in categorical data. The major possibilities of categorical data are to prepare pie charts, bar charts or to simply count the number of observations and find percentages. Meanwhile, numerical data are data collected in number format. The possibilities of analysis with numerical data are comparatively higher than categorical data. With numerical data, algorithms can be prepared to find the mean, median, mode, range, quantities, variance, standard deviation, coefficient of variation, histogram, box plot, kurtosis and skewness.

Similarly, bivariate analysis is the process of analysing two variables of attributes simultaneously. The concept of simultaneous analysis on the behaviours of two attributes, and related relationship verifies the required associated strength. This also includes the verification of discrepancies between two attributes and the consequences of this discrepancy. As bivariate analysis consists of two attributes, there are three sub sections of bivariate analysis: categorical and categorical, numerical and numerical, and categorical and numerical.

Categorical and categorical analysis is conducted on two types of categorical data. Categorical data are data that do not have a specified numerical quantity (e.g., name, cities, counties). Data are analysed by plotting a Ch^2 test, Bar chart or 2-Y axis plot. The second type of bivariate analysis is numerical and numerical. In this type of analysis, the two attributes of the analysis are finite elements or quantities (e.g., salary, temperature, pressure). Here, the attributes are analysed in a correlation manner or scatter plot manner. The last type of bivariate analysis is categorical and numerical. In this type of analysis, one attribute is analysed against other types of attributes (e.g., the name of an employee against the number of experiences he has in a similar field or temperature of a machine against the factory name). This type of analysis can explore or explain past data. Future modelling or predictions are explained in subsequent sections.

#### 2.4.3.1.2 Prediction Classifications

Predicting an unexpected outcome from a data set is called predictive modelling. Outcomes are often referred to as data models, which are obtained using previous data and statistics. These models can be used with any kind of data (Jose & Mini, 2017) to accomplish anything from predicting the number of viewers of an upcoming show to studying the behaviour of a machine using data from sensors. Such models are important for predicting the outcome of upcoming events. Predictions and classification methods are outlined in Figure 6.

Predictive models based on detection theory are used to assess probability (Barreto-Sanz, Bujard, & Peña-Reyes, 2012). The amount of data collected is directly proportional to the accuracy of the prediction. For example, based on the title tag the inbox is filtered. Due to spams and other related junk the model accuracy is diluted. Models have a definite boundary that is in sync with synonymous or overlapping data. These models are referred to by various definitions depending on the context (Trabelsi, Vahedi, Komurcugil, Abu-Rub, & Al-Haddad, 2018). They are referred to as ‘ML’ in a research or academic context, while ‘predictive analysis’ is the standard name for industry experts. Multiple ways of modelling can be implemented for the type of data available. As discussed in the previous section, there are two data types: categorical and numerical.

Modelling categorical data is often referred to as ‘classification’. In this type of data analysis, predictions are either on a target or a set of class. Models can be built based on one or more categorical attributes with multiple options. Four kinds of analysis are possible for the classification type: classification by frequency table, covariance matrix, similarity functions and others (Kristoffersen & Holden, 2017).

Frequency table is a type of classification in which the frequency of observations is mapped according to classifier of the observations. There are four main methods of classification: ZeroR, OneR, Naïve Bayesian and decision tree. ZeroR counts on the target by ignoring all other predictors and predicts the class on a majority category. One Rule or OneR is highly simple and is the most accurate of the classification algorithms. This algorithm generates an individual rule for every predictor in a given data set, which in turn selects the smallest overall error called 'one rule'. The next classification family is Naïve Bayesian. This set of algorithms is easy to implement on a large number of data sets because it lacks multiple iteratives, which makes models highly complicated. The last type of classification is decision trees. Decision trees are built in the model of a tree by the classification algorithm. This type of classification breaks a given data set into two major sections and then further divides the data set unless it reaches the predictor. These trees can handle categorical and numerical values.

Regression is a mathematical modelling method used to predict an accurate value (numerical value) by constructing models based on one or more than one predictor, such as numerical or categorical data. Regression follows the same set of subsets in predicting values as classification. These algorithms are more accurate in terms of predicting a value if the data set is filtered for missing values and corrupted data. A cluster is a collection of data that is comparable in some way. Clustering (also known as unsupervised learning) is the act of breaking a dataset into groups with individuals that are as similar or similar to one another as feasible, while distinct groups are as dissimilar or far apart as possible. Clustering can reveal correlations in a data collection that were previously overlooked. Cluster analysis has a wide range of applications. Cluster analysis may be used to uncover and characterise consumer categories for marketing reasons in business, and it can be used to categorise plants and animals based on their characteristics in biology. All sets of items (item sets) with support greater than the minimum support are found using association rules, which then use the big item sets to construct the needed rules with more confidence than the minimal confidence. The lift of a rule is the difference between the actual and predicted support if X and Y were independent. Market basket analysis is a good illustration of how association rules may be used.

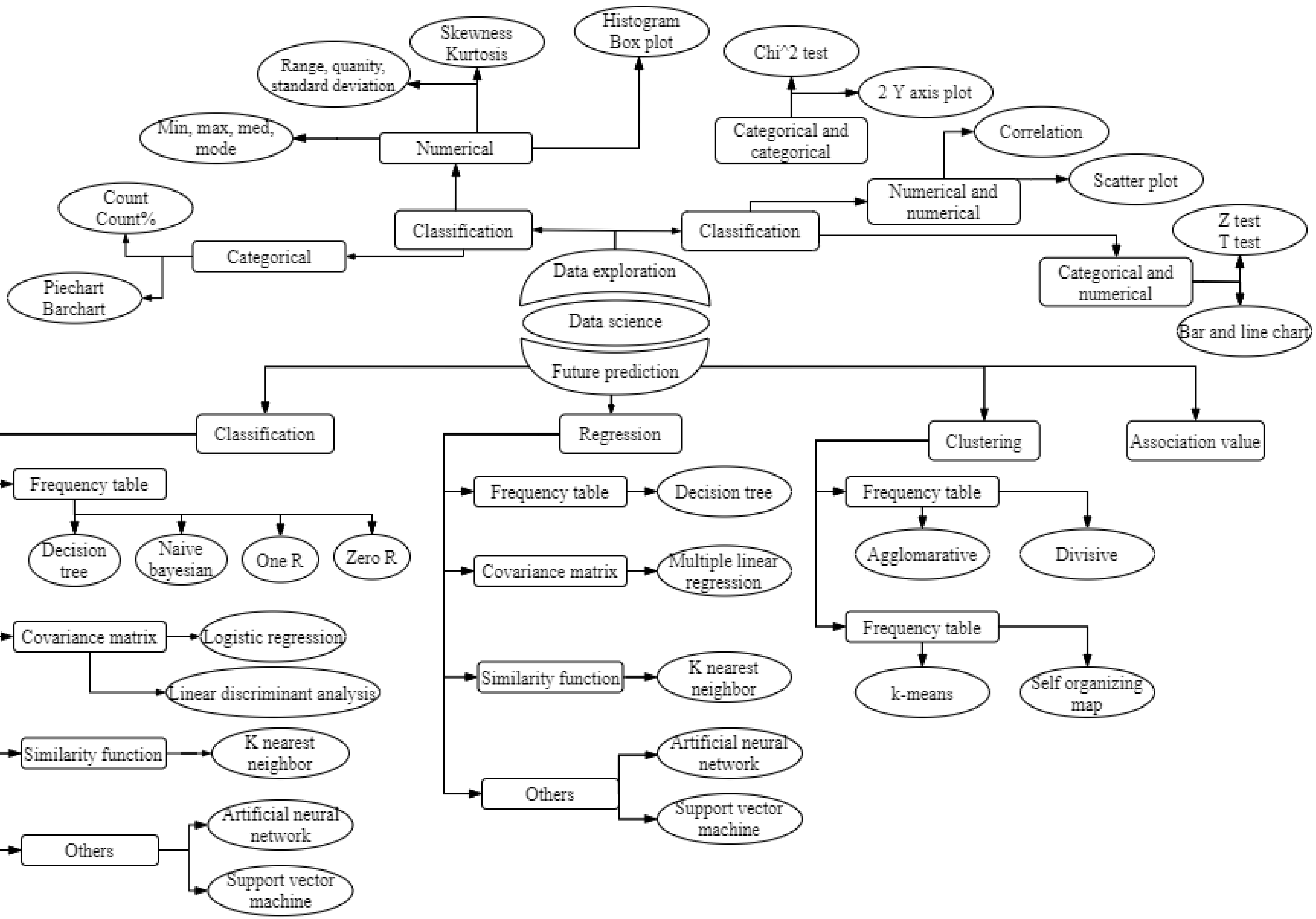


**Figure 6 Data science methods**

### 2.4.3.2 Anomaly Detection Methods

Recently, AD in high-dimensional (HD) information, particularly in real-world scenarios and applications, has become a key research problem. Existing AD methods fail to maintain adequate accuracy due to the abundance of information produced by diversified sources. This greatly affects the AD performance and its accuracy in practical applications. In practical domains, specifically in the manufacturing sector, large chunks of information are generated. As manufacturing systems involve multiple operational phases and processes, they may encounter anomaly intrusions in real time. However, in this sector, AD is highly complicated due to the plethora of data produced by distinct operational processes. Exploring the concrete difficulties introduced by AD with HD data is important to clearly identify the core issues and bridge this gap. Therefore, this research studied the generic state of AD in HD data and presents the available AD methods used to recognise anomalies in the industrial and manufacturing sectors, among others. An outlook on AD in HD data is provided, along with an explanation of the high-dimensionality issue. Further, the research on AD is reviewed. Lastly, this research identifies the heterogeneous impediments induced by AD in HD data to underscore the need to develop better AD schemes capable of precisely and swiftly recognising anomalies involved with HD data.

AD is one of the most widely researched problems within heterogeneous applications domains and research areas (Chandola, Banerjee, & Kumar, 2009). AD typically involves determining patterns in information that deviate from anticipated behaviour. Non-conforming patterns are known as anomalies, discordant observations, outliers, aberrations, exceptions, contaminants or peculiarities in distinct application fields. AD assists in tracking the status of the ordinary daily activities of every network, application or system. Anomalies are induced by malicious activities. Straightforward AD involves defining a region characterising normal activity and declaring any observation that does not match with the normal activity region as an aberration or anomaly. However, certain key issues make this perceptibly straightforward method quite challenging. As malicious activities induce anomalies, often vicious adversaries make the anomalous activities appear normal, thus making it more difficult to identify abnormal activity. In different fields, normal behaviour or activity is continually evolving. The notion of what constitutes an anomaly differs in different fields. For instance, in healthcare, an anomaly can be a slight deviation from the standard activity (body temperature fluctuations), while in the stock market, slight deviations (stock value fluctuations) are considered normal. Therefore, an AD method developed for one field may not work in another field. In light of this, the challenges surrounding AD are not easily addressed.

AD in high-dimensional (HD) information is another prominent research problem (Thudumu, Branch, Jin, & Singh, 2020a). Dimensionality indicates the number of variables, attributes or features within datasets. The rise in information dimensions poses a critical challenge for AD in giant databases. The manufacturing and industrial sectors frequently work with giant data sets. As these sectors involve multiple operation processes, they generate large amounts of data. Therefore, the HD information produced may be prone to anomalies, as illustrated in Figure 7. It is largely infeasible to cautiously execute every process without anomaly intrusion within these sectors. Despite safety precautions and technological improvements in the industrial and manufacturing domains (Jwo, Lin, & Lee, 2021; Kotsiopoulos et al., 2021; Moreno-Rabel & Fernández-Mu Noz, 2016; Qu, Ming, Liu, Zhang, & Hou, 2019), operations processes can encounter anomalies in their working phase. Detecting these aberrations directly using generated HD data is a sophisticated and time-consuming task. HD data may comprise redundant data along with meaningful or useful information for AD. Manually separating redundant information from meaningful information can be a tedious task. However, isolating such data from HD information is essential for AD. Recently, ML and deep learning (DL) techniques have been proposed for AD and HD data reduction (Dogan & Birant, 2021; Erfani, Rajasegarar, Karunasekera, & Leckie, 2016; Kasun, Yang, Huang, & Zhang, 2016; Pang, Shen, Cao, & Hengel, 2021b). This research investigates AD in HD information, its challenges, the heterogenous techniques adopted for AD and the vital changes needed in AD using HD data for future applications.

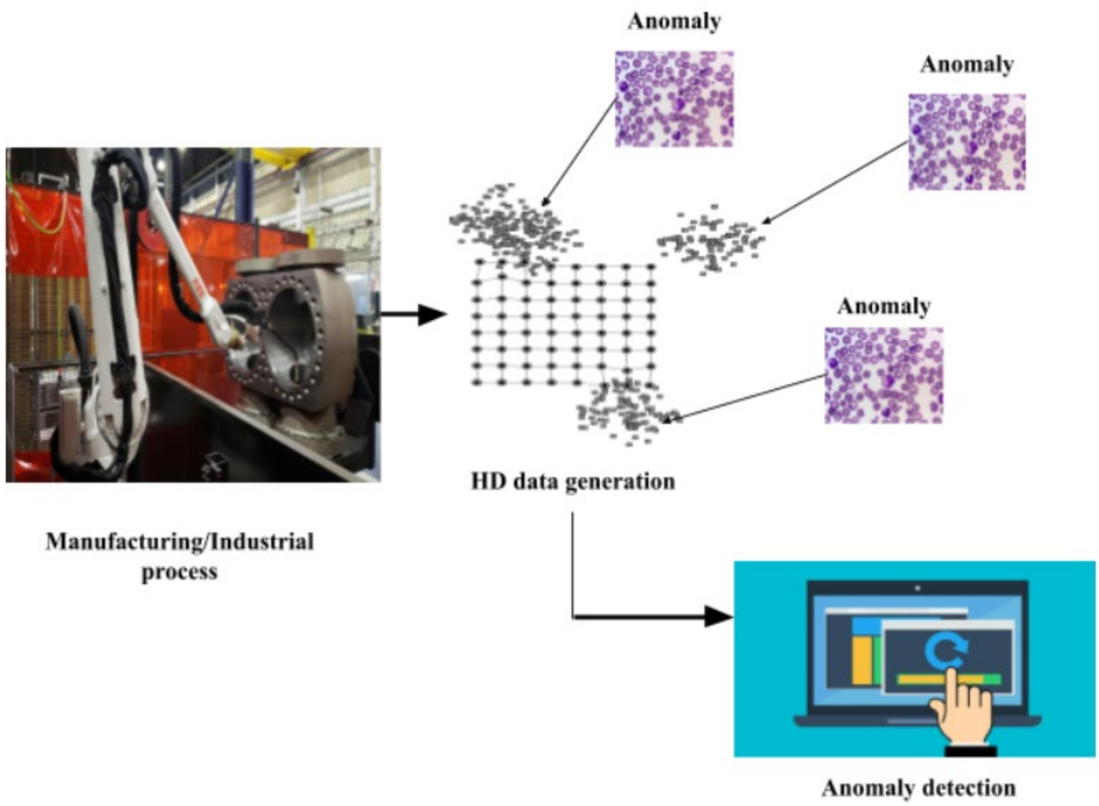


**Figure 7 Overview of anomaly detection**

### 2.4.3.3 Benchmarking Anomaly Detection

AD in HD information has become a prominent research area due to its miscellaneous applications in the real world (Ahmed, Mahmood, & Hu, 2016; Das, Adepu, & Zhou, 2020; Lindemann, Maschler, Sahlab, & Weyrich, 2021; Rosa et al., 2021). (Chandola et al., 2009) provided a taxonomy and survey of diverse AD methods for miscellaneous applications, such as sensor networks, intrusion detection and identifying manufacturing defects and unusual behaviour patterns. The authors described the fundamentals, advantages and pitfalls of diverse AD techniques and outlined the issues associated with AD. (Thudumu, Branch, Jin, & Singh, 2020b)) presented a generic survey of AD methods for HD big data.

The strategies for tackling huge dimensionality issues were examined. The critical difficulties encountered by AD in HD data were identified. This work highlighted the need for improved AD strategies capable of tackling vast-dimensionality data problems. (Lindemann et al., 2021) presented and compared two data-oriented self-learning schemes adopted for AD within vast quantities of process and machine data. Frameworks for machine behaviour monitoring were developed to capture complex correlations and acquire attributes signifying the anomalies, and the results were evaluated using practical industrial data gathered from metal manufacturing processes. (Ahmed et al., 2016) described four prime classes of AD schemes, including clustering, information theory, statistical and classification. Diverse schemes used for anomaly categorisation were also presented. The classes of AD schemes described were compared and contrasted considering complexity, output and attack priority parameters to evaluate their performance and suitability for AD.

A general survey of AD methods was presented by (Patcha & Park, 2007). The authors explained the critical technological trends involved in AD, the heterogenous challenges faced by AD methods, open issues in AD and existing panaceas. (Jiang, Cui, & Faloutsos, 2016) evaluated various schemes for suspicious behaviour identification and outlined supervised techniques, graph-based techniques and clustering techniques used to detect dubious activities. (Gupta, Gao, Aggarwal, & Han, 2014) explored various outlier identification methods for temporal information and data. The authors provided a structured and comprehensive outline of a large set of attractive outlier definitions, particularly for various sorts of temporal data, application scenarios and novel techniques. ( Habeeb et al., 2019) subsequently discussed real-time massive information processing for AD and reviewed the cutting-edge information processing technologies pertinent to AD. The authors also explored diverse ML schemes for AD, reviewed ML-enabled massive information processing methods for AD and identified important research barriers in real-time colossal information processing schemes for AD.

Several DL and ML-oriented network AD techniques were presented by (Kwon et al., 2019). The authors showed that DL techniques have highly promising outputs with high accuracy in identifying anomalies when contrasted with commonly adopted ML methods. (Zimek, Schubert, & Kriegel, 2012) examined certain common issues associated with HD data and the issues encountered in outlier recognition. The authors further investigated the diverse unsupervised techniques for outlier identification in HD numerical data and the outlier identification techniques belonging to two distinct classes (namely, techniques considering subspaces and techniques not considering subspaces while defining the outliers). The authors suggested the need for key improvements in outlier recognition schemes, particularly for HD data. (Aggarwal, 2017) studied the scope of the subspace technique for HD outlier detection and showed that the outlier examination process could be significantly sharpened by searching for the subspaces containing data points that deviated significantly from ordinary or normal behaviour. (Angiulli & Pizzuti, 2005) proposed an algorithm for efficiently identifying the top outliers in HD and large data sets. The algorithm employed involved two stages: the first provided a close solution with spatial cost and temporal cost, while the second provided an exact solution. The algorithm showed great scalability with regard to data set size and dimensionality.

#### 2.4.3.4 Anomaly Detection in High-Dimensional Data

AD is an important approach for recognising dubious activities, fraud activities, network attacks and other unusual events that may exert adverse effects on ordinary operations. The prime significance of AD is that information is translated into vital actionable data, and valuable insights are revealed (Chandola et al., 2009). HD datasets contain thousands or millions of independent features, components and variables. Analysing data in HD datasets is highly complicated due to increased dimension, dynamicity and variability. Increased data dimensionality leads to data sparsity, making the process of data analysis more tedious. Data analysis is paramount for AD in any mechanism. Under such circumstances, traditional techniques for identifying anomalies in HD space become unsuitable and surplus due to increased data sparsity. AD methods can be applied in offline or online modes to address high-dimensionality issues. Typically, anomalies offline are identified using historical databases, while online, fresh data points are introduced continuously as anomalies are identified. Determining the global maxima of HD datasets is difficult due to isolated and scattered data points. The problem of high-dimensionality can be handled smoothly by reducing the features of HD datasets ( Avendano, Caljouw, Deschrijver, & Hoecke, 2021; Song, Yang, Siadat, & Pechenizkiy, 2013). Thus, AD techniques should be integrated into improved dimensionality reduction schemes to effectively detect anomalies in HD data.

#### 2.4.3.5 Anomaly Detection Techniques

AD in industrial control mechanisms was discussed by (Das et al., 2020), who presented a rule-directed approach to recognising anomalies. A performance examination of the proposed rule-oriented approach showed strong accuracy compared with diverse competing techniques. ( Avendano et al., 2021) outlined an approach to AD in a cold forming manufacturing procedure that effectively detected anomalies and showed greater robustness. The approach used fewer training parameters and required no expert knowledge regarding the components' physics. (Scime & Beuth, 2018) presented AD in an industrial manufacturing procedure and discussed a method for the in-situ supervision and examination of anomalies in a laser powder bed (LPB) additive manufacturing procedure. Anomalies that occurred during the powder dissemination phase of the manufacturing procedure were recognised and categorised effectively using ML and a computer vision fusion scheme. ( Zhou, Hu, Liang, Ma, & Jin, 2020) proposed a variational long short-term memory (VLSTM) framework for AD in industrial HD data. The VLSTM framework included a compression system and an estimation system. The compression system used an LSTM encoder unit, LSTM decoder unit and a variational reparameterization unit to alleviate the complexity of the HD raw information without losing significant features. The estimation system was fed with an improved feature representation to identify anomalies in industrial HD. The experimental outcomes showed that the VLSTM efficiently handled the imbalance and HD data problems, reduced the false score in AD and significantly enhanced the accuracy.

(Z. Li, Li, Wang, & Wang, 2019) proposed a hybrid DL model employing LSTM and stacked autoencoders for AD in mechanical apparatus. The proposed LSTM and stacked autoencoders approach had two vital stages. The first stage involved multiple features series representation using stacked autoencoders, while the second involved AD using LSTM. The LSTM and stacked autoencoders technique could recognise anomalies in a fully unsupervised learning background via multiple features series, even with unlabelled history data and an absence of empirical knowledge regarding the anomaly, detecting anomalies with a superior accuracy of 99%. Moreover, it offered a substitute approach for integrating and leveraging features for AD without practical or empirical knowledge. (Zhao, Liu, Wang, & Liu, 2014) outlined another approach to AD in an energy system in the steel industry. Considering the dynamic attributes of energy data, an adaptive fuzzy clustering method was employed for AD. The experiments were conducted using real-world energy information arriving from a steel plant. The results showed that the adaptive fuzzy clustering scheme exhibited good performance and had greater precision than other AD techniques.

(Zhang, Lin, & Karim, 2017) proposed an AD technique from HD information streams that aimed to detect faults from non-stationary HD data streams. The authors outlined an angle-directed subspace AD technique for detecting low-dimensional faults from HD datasets. The fault-pertinent subspaces were selected by assessing the vectorial angles, and the object's local outliers were computed. By exploiting a sliding window method, the proposed technique was extended to an online mode to ceaselessly monitor the system states. A comparison of the proposed technique with the standard outlier factor-directed approaches showed that the proposed technique had greater efficacy and accuracy. Moreover, it could discriminate low-dimensional subspace anomalies from ordinary samples in HD spaces. (Salehi, Leckie, Bezdek, Vaithianathan, & Zhang, 2017) presented a rapid local outlier (LO) identification technique in HD data streams. The proposed LO detection scheme was highly suitable for memory-constrained and HD information streams involving application environments and showed higher accuracy in LO detection and greater robustness to data changes in HD data. Meanwhile, (Wu, Song, & Moon, 2019) discussed AD in computer numerical control milling machines and 3D printing machines using AD algorithm, random forest (RF) and K-nearest neighbours (KNN) schemes. Vision and an acoustic signal were employed as the physical information sources for the 3D printing procedure and the computer numerical control milling procedure, respectively. Of the KNN, AD algorithm and RF schemes, the AD algorithm showed highest accuracy in identifying anomalies in the 3D printing procedure, while the RF scheme showed the highest accuracy in recognising anomalies in the milling procedure. (Soni, Gopalan, & Varadharajan, 2016) presented operational and electrical AD by examining variations in the electrical variables acquired from energy meters. The load information was acquired from a small manufacturing facility by installing energy meters at diverse load points. After pre-processing the raw information, the necessary attributes were extracted to identify possible anomalies. The anomalies were categorised as operation-, device- or source-based anomalies depending on their origin.

(Vávra, Hromada, Lukáš, & Dworzecki, 2021) presented an adaptive AD system using ML algorithms for industrial control scenarios. The authors provided an adaptive remedy for cybernetic protection in industrial control mechanisms. The proposed AD system exploited multiple ML techniques for AD and was a strong and an adaptable system capable of meeting the requirements of industrial control mechanisms. (Demertzis, Iliadis, Tziritas, & Kikiras, 2020) outlined a blockchain, DL-oriented method for AD in industrial settings. Through smart contracts, a two-sided traffic control contract was implemented to recognise anomalies. This approach was shown to be a safe, distributed platform for supervising and completing related transactions in decisive infrastructure networks. In a neoteric DL approach for AD was proposed. A convolutional neural network was employed to categorise multiclass anomalies. The adopted DL approach displayed outstanding AD performance compared with available DL implementations. (Quatrini, Costantino, Di Gravio, & Patriarca, 2020) presented a methodology for AD using real-time information from a multistage industrial process. A two-step approach was adopted wherein the initial step involved identifying the ongoing process stage and the next was to classify the data as 'critical', 'warning' or 'expected' for AD. The methodology showed high suitability for AD in machines performing several functions without the testimony of production stages. The results showed that the adopted two-step approach exhibited greater precision in AD. (Saci, Al-Dweik, & Shami, 2021) proposed an autocorrelation-based low-complexity technique for identifying anomalies in steel manufacturing operations. The authors employed the diverse vibration measurements gathered from various in-built sensors for temporal correlation computation using an autocorrelation function. This autocorrelation-based technique outperformed other ML techniques in AD with reduced execution and training time benefits.

The different AD techniques listed in Table 2 are categorised as rule based, ML, DL and other, as represented in Figure 8. As shown in Figure 8, among the commonly used schemes (namely, rule-based, ML and DL), ML has been examined the most in the reviewed works.

**Table 2 Existing anomaly detection techniques**

| References | AD techniques | Applications |
|---|---|---|
| **(Das et al., 2020)** | Rule-based scheme | Industrial processes |
| **(Nieves Avendano et al., 2021)** | Rule mining | Cold forming manufacturing |
| **(Scime & Beuth, 2018)** | ML, Computer vision | LPB additive manufacturing |
| **(Zhou et al., 2020)** | VLSTM | Industrial processes |
| **(Li et al., 2019)** | LSTM and stacked autoencoders | Manufacturing processes, industrial processes |
| **(Zhao et al., 2014)** | Adaptive fuzzy clustering | Industrial processes |
| **(Zhang et al., 2017)** | Angle-directed subspace, sliding window | Industrial processes |
| **(Salehi et al., 2017)** | LO detection scheme | Manufacturing processes, industrial processes |
| **(Wu et al., 2019)** | AD algorithm, KNN, RF | Printing processes, computer numerical control milling procedures |
| **(Soni et al., 2016)** | ML | Energy-related manufacturing |
| **(Vávra et al., 2021)** | ML | Manufacturing processes, industrial processes |
| **(Demertzis et al., 2020)** | DL | Industrial processes |
| **(Pang, Shen, Cao, & Hengel, 2021a)** | Convolutional neural network | Manufacturing processes, industrial processes |
| **(Quatrini et al., 2020)** | - | Industrial process |
| **(Saci et al., 2021)** | Autocorrelation-based scheme | Steel manufacturing operations |

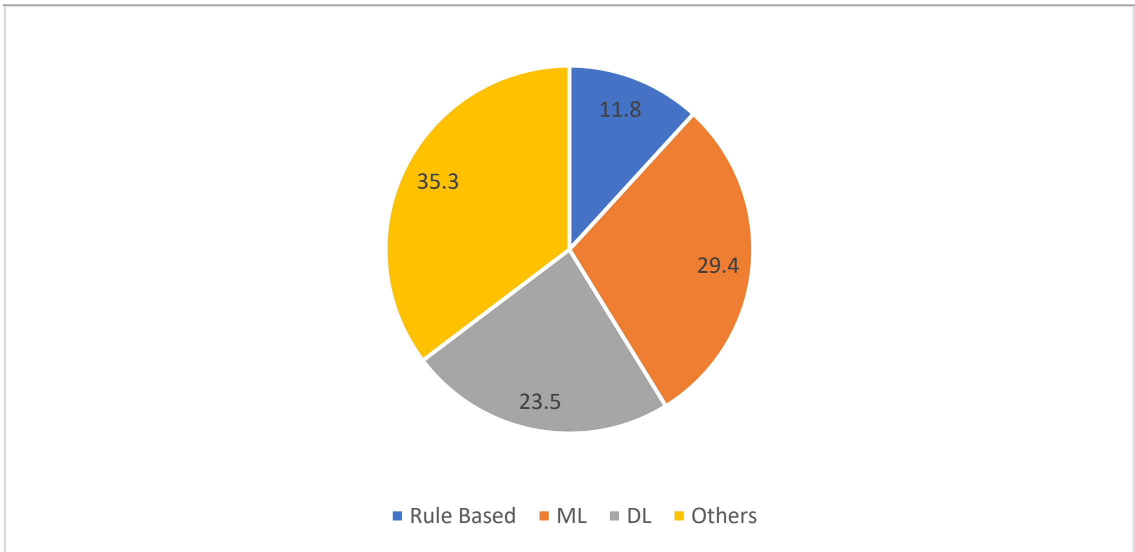


**Figure 8 AD techniques**

#### 2.4.3.6 Challenges and Gaps

After a thorough study of self-learning algorithms, below were the major findings:

i) The increasing tendency of practical or realistic applications towards data-driven control, coupled with the lack of availability of generic approaches for AD in HD data, has made the high-dimensionality problem and its repercussions for AD inevitable in practical scenarios.

ii) The vast dimensionality problem has in turn led to weak AD accuracy and high computational complexity. This problem has not just created challenges in identifying anomalies or unusual behaviour but has also introduced additional difficulties in ensuring smooth operations and task accomplishment. In events involving HD data, AD methods falter due to constrained computational potential and related factors, thereby resulting in performance degradation.

iii) Recognising anomalous information points across colossal databases generated by real-world operations, such as manufacturing or industrial processes, has become highly complicated and is made worse by the ceaseless arrival of unbounded bulk data streams. As abundant data are involved in these processes, some information may be redundant or unrelated to AD. However, filtering surplus information from bulk streams and selecting only the needed data can be time consuming and difficult.

iv) Moreover, conventional AD techniques are no longer effective at achieving effective AD in HD information. Prior research has addressed the limitations of AD techniques regarding high-dimensionality issues individually or separately but not comprehensively or jointly. Thus, better techniques for addressing both AD and high-dimensionality challenges simultaneously are needed to overcome the aforementioned challenges.

## 2.5 Positioning of Contributions

In previous sections, manufacturing challenges as well capabilities of transformative technologies to potentially address were discussed. Similarly, research on SM has suggested that advanced manufacturing using smart technologies can improve efficiency, decision-making frameworks and low-volume manufacturing. Due to the heterogenous nature of these technologies, integrating them in a single framework requires separate in-depth analysis.

The relationship between ML, CC and DT must be seamless so that tasks that have been originated are executed in real time without interruption. Task scheduling and executing needed a firm communication between physical and virtual shopfloor. As shown in Figure 9, the research methodology pinpointed the gaps and challenges within the manufacturing industry by conducting case studies and field research. This study was necessary in light of the practical problems associated with the industry to identify the correct direction of implementation. As previously outlined in the research, integrating technologies to address inefficiency in manufacturing, decision-making frameworks and low-volume manufacturing is the key contribution of the present work.

The individual section 3 of this thesis describes the outcomes of the field study, challenges and the framework depending on the field study results. Finally, the

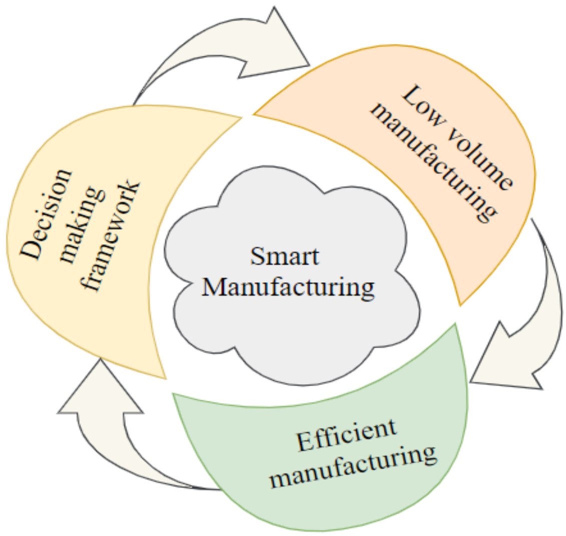


**Figure 9 Research contributions**

implementation strategies are outlined, and results obtained from the implementation are discussed. Each chapter of the thesis builds a complete picture of SM, beginning with the research problem statement to the implementation and outcomes discussed in the final chapter.

Implementation strategies were modified and made accessible to other similar manufacturing companies. The framework introduced is not limited to the company that featured as the case study. Low-volume production was addressed when integrating CPS into the framework. Similarly, ML and AD were introduced and modified to improve efficiency. The improved implementation addressed the challenges of decision-making strategies and seamless manufacturing. Figure 10 depicts the methodology adopted in the research.

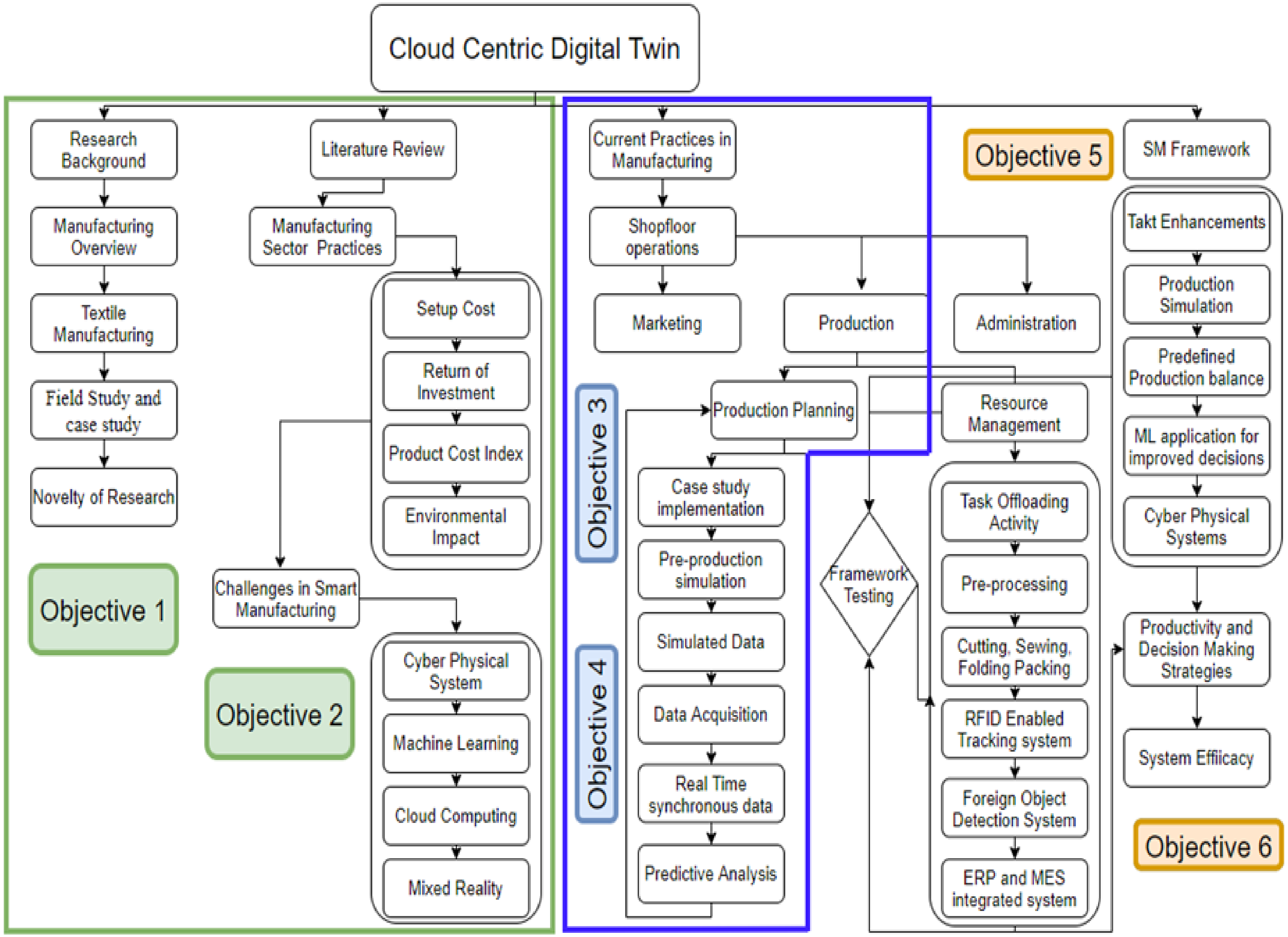


**Figure 10 Research methods**

## 2.6 Chapter Summary

This chapter outlines the concept of SM, traditional approaches in textile manufacturing and the key research areas identified in the literature review. The following major findings from the literature were made:

i) The initial part of the LR detailed current trends in manufacturing and SM practices. Manufacturing plays a vital role in the Australian economy, equating to $100 billion in value. Further, the Australian manufacturing industry employs more than 1.27 million people. The manufacturing industry has faced many challenges. Challenges in manufacturing practices include complex behaviours in manufacturing, communication issues and inefficiencies. In the present research, a detailed analysis of practices across the textile industry was conducted to explore relevant contributions and challenges. Advancements in manufacturing lack implementation strategies, particularly in textile manufacturing. The industry must produce personalised products in a low-volume environment. This implies a hand-crafted industry, representing complex heterogeneous operational characters that are difficult to integrate and control for various operations. Furthermore, there required an appropriate interfacing module that needed to interconnect production planning, admin responsibility, marketing and sales and resource management.

ii) Several challenges were identified during the LR. The first is that the control of machine characters results inefficiencies related to increased costs, aside from the high Australian labour prices, the second is the demand for inclusive product personalisation due to global market competitions and the third is effective communication within roles and machines, resulting in waste. These challenges explained why Australian manufacturing has lagged behind in terms of global competitiveness.

iii) The LR suggested that SM is a potential solution to the challenges faced by the textile industry. SM was frequently discussed by researchers, though there was a lack of practical implementation strategies. The literature suggested implementation of SM in singularities with limited applications (e.g.: sensor output for an operation simulated). The LR revealed a lack of integrated multiple transformative technologies used for Industry 4.0 application in manufacturing industry. In the literature reviewed, connecting takt time, cycle time and operational costs for efficiency gains as an integrated approach was not discussed.

iv) Transformative technologies were used to capture manufacturing operations, and AR/VR technologies were used to visualise the operational flow and conduct a takt time analysis and simulation. These inputs helped attain vital data that were used to analyse the behaviour of the machines by incorporating ML algorithms for PA. These tools, integrated in a cloud platform, show potential for addressing the aforementioned manufacturing challenges. Once the integration of technologies has been migrated to the cloud, the cloud handles the operations using high-end computational programs. Based on the reviewed literature, a conceptual framework was proposed and is implemented in the next chapter.

v) SM-integrated approaches from previous research lacked decision-making analytics and, consequently, communication was identified as major concern. This lack of communication was due to absence of framework to automate communication using data analytics. Collaboration between different roles and machines using advanced tools was found to lack the required integration in existing practices. New trends in wireless communication have given a broad understanding to the real-time integration of the digital and physical world. Seamless data transfer and the integration of tools have made the manufacturing process more efficient and effective compared with traditional practices. Along with communication, advanced technologies for prioritised computing and offloading tasks are missing. While these ideas have been illustrated theoretically, practical implementation is lacking, particularly in the textile industry.

vi) A major element of SM involves predicting the complex behaviours of machines. These behaviours and their controls are the major challenges of enhancing production process efficiencies significantly. Due to the complex parameters involved in controlling machinery, it is often difficult to make a characteristic prediction (e.g., machine failure). This produces inefficiencies, such as a prolonged work lag, which affects the manufacturer. The LR revealed that ML algorithms were able to capture machine characteristics. Hence implementing these ML to add intelligence was main theme of this research.

# 3 Manufacturing Field Studies

This chapter details the methods applied in the field study that was conducted on Australian manufacturing company SleepCorp Pty. Ltd. SleepCorp is a mattress protector manufacturing company that has complex manual operations. This was an ideal case study for demonstrating the SM framework. If the efficacy of the framework can be demonstrated in this industry, it can also be applied in other industries, with minimal changes to the framework.

## 3.1 Introduction

In this chapter, a manufacturing framework that underpins the manufacturing challenges discussed in previous chapters is conceptualised. This chapter outlines a conceptual framework of real-time computing and discusses CC algorithms for data analytics and predictions. The framework and proposed setup of data accumulation for exploring the behaviour analysis are discussed. This chapter:

i) develops real-time computing for a manufacturing line that has a complex nature and convoluted characters. A conceptual framework was modelled adopting transformative technologies plotted to underpin the challenges, limitations and advantages. These steps helped understand the product artefacts, imprint ideas on a practical implementation blueprint and compare alternative concepts proposed by other researchers. The proposed concept was evaluated with the following parameters: economic benefits of implementation and usability and space optimisable solutions to increase production density.
ii) chooses between the best possible layouts and concept to demonstrate the real-time computing. The use of VR and AR was proposed with real machines and a real factory layout to simulate a realistic approach.
iii) defines later stages of the proposal with the data accumulation setup and outlines a sophisticated and reliable way of implementing the concepts in a real manufacturing line.

This section introduces the state of the art of the physical shopfloor and discusses the machines involved in the manufacturing line of a textile manufacturing company, 3D modelling software, the simulation setup and the test bed results.

## 3.2 Operational Analysis

Efficiency enhancement appears possible with CPS on cloud-enabled infrastructure. CNR, as first described by (Kuffner, 2013) takes advantage of cloud robotics and wireless technology, which have elevated the potential of integrating autonomous sensing and actuation in evolving dynamic and complex industrial applications. Following the three revolutions of mechanisation, mass production and digitisation, Industry 4.0 has brought incipient autonomous technologies into the industrial realm, transforming traditional factories into the smart factories of the future (Biesinger, Meike, Kraß, & Weyrich, 2018).

Due the attributes of virtualisation, decentralisation and real-time capability, Industry 4.0 was envisioned as a key way of combining these robotic and manufacturing technologies (Jawad et al., 2019). For instance, CC and wireless sensors are required for automating manufacturing applications (e.g.: sensing, actuating and monitoring) (Stock et al., 2019). Industrial cloud robotics encapsulate the design principle of robotic resources integrated with cheaper computing costs and network resources. This has extended operational capabilities and shifted robotic and manufacturing applications away from carrying out repetitive tasks towards solving more complex multi-objective problems in uncertain manufacturing environments (Papazoglou & Elgammal, 2017). While CNR opens up the possibility of using robotic networks to further automate industrial processes, it also adds significant complications in terms of decision-making and coordination. As previously mentioned, cloud services can be leveraged to enhance the performance and efficiency of a system (Yao et al., 2018).

As CC is a well-established entity, the overall efficiency of updated SM can be increased by integrating CNR, XR and ML algorithms. Integrating aforementioned technologies in newly developed/proposed SM operations increased overall efficiency. These technologies are prominent in their respective fields. However, this research aimed to propose the framework to integrate them in a single platform. This is further aided by DT, which paves the way for the smooth integration of the physical and cyber world in the context of the manufacturing industry. While AR/VR provides virtualisation for the preparation of the product manufacturing, DT can emulate real-time applications and run them in real time, facilitating the analyses of changes that the physical equipment can react to for modification purposes. Thus, SM can help prepare rigid manufacturing processes that perform efficiently and accurately from preparation through production and maintenance of the operation.

It is important to understand the basic requirements of the technologies in question. For example, CNR technology uses a range of robots, such as mobile robots, stationary robots and cloud facilitates, to interact with the system components. AR/VR systems consist of sensors, displays and dedicated software. This research focuses on efficiently transferring CNR and AR/VR onto a single platform to fine-tune and improve the performance of SM, with additional real-time analytical support provided by DT. Given the challenges of integrating these technologies, the novelty of this work lies in its laying of a framework for virtually created robots to interact with the virtual cloud and perform tasks assigned to them via the cloud. Here, the virtual machines in the cloud work according to their scheduled tasks and workload. These tasks were taken into consideration according to priorities and were performed with the First-In-First-Out algorithm. This integration plays a critical role in achieving an efficient SM framework. The study was conducted in two stages. First, a conceptual framework was proposed to integrate CNR and AR/VR on a platform for cloud-empowered SM with real-time support from DT. The ambiguities were presented, and hardware and software solutions related to the implementation of the cloud-centric DT paradigm were developed. Second, the case study on an automated mattress protector manufacturer was presented to highlight the components of the integrated system to complement the proposed framework. This was followed by a proposal for a hybrid assembly line operation for a modelled DT to demonstrate the approach in the context of a real-time industrial application.

### 3.2.1 Conceptual Framework

The textile indsurty was used as a test bed in this research, as it represented a typical manufacturing paradigm with various complex operations  as well vast individualiased product demands. Further, textile manufacturing was SME, representative of the Austrlain manufacturing. The heterogeneous characters of the textile industry include ongoing changes to processes, resources and structures. Potential triggers for changes to existing manufacturing processes are new products, changing requirements, new technology and model upgrades. Implementing changes in a real manufacturing context requires the strategic overhaul of interlinked disciplines. Existing practices are unable to capture these complex characteristics. Ambiguities arise due to manual interventions, resulting in increased waste and cost. These issues were addressed with an SM environment using a DT paradigm. The conceptual DT framework was modelled as interconnected to CPS, as shown in Figure 11. DT was remotely connected to the library and hardware systems (e.g., machinery). The data library stored pre-planned data, order status and postproduction data and was accessed by CPS through a cloud platform. A hardware system provided machinery commentary and CNR data through sensors via the cloud platform to the CPS system. CPS integrated the hardware–software platform through cloud networks. The CPS set of embedded systems communicated and interacted bi-directionally. The cyber element of the CPS also monitored and controlled the input/outputs from physical entities. DT reflected the current state of machinery and could incorporate required changes. Further, DT provided an interface for simulation and analysis to identify optimal solutions.

### 3.2.2 Digital Twin

Further development of DT was made for the shopfloor representation of manufacturing processes to develop a streamlined workflow, as shown in Figure 11. The model consisted of a physical shopfloor connected to a virtual shopfloor through a cloud-centric platform (Biesinger et al., 2018).

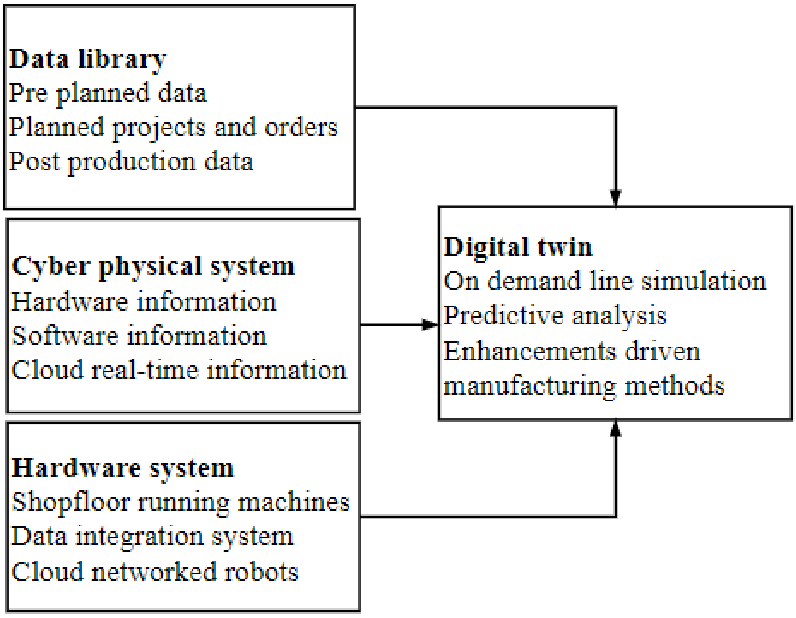


**Figure 11 Conceptual framework of digital twin**

The physical shopfloor integrated physical entities, accepted instructions and performed instructional tasks. The components mainly included machine tools, robot entities, resources and sensory nodes (e.g., temperature and pressure) (Wu et al., 2019). Sensory IoT capabilities captured heterogeneous characteristics from multiple sources for real-time perception. The virtual shopfloor consisted of various AR/VR virtual models, manufacturing attribute models, behaviour-rule models and data-fusion models in a simulated environment (Gao, Lv, Hou, Liu, & Xu, 2019).

The cloud platform provided large data set storage and communication capabilities, integrating the physical and virtual shopfloors in a DT paradigm (Yao et al., 2018). These technologies mainly included wireless communication links with industrial IoTs, industrial sensors, industrial wireless network, CNR and mobile devices. Cloud-enabled data management integrating manufacturing, machines, materials, quality, cost, resources and environmental data (Ribeiro & Björkman, 2018).

DT integrated shopfloor data systems from the production planning phase to the running of the real-time simulation, thus providing analytics for enhanced system performance. The analytical support for decision-making included task scheduling optimisation, real-time monitoring of manufacturing resources, quality monitoring, material allotting optimisation and PM.

## 3.3 Field Study

This section describes a case study of textile manufacturer (e.g.: mattress protector manufacturer SleepCorp Pty. Ltd). Textile manufactures mattress protectors in more than 1,000 product portfolios and, to date, has traditional manufacturing practices. The manufacturer has several craft operations, such as cutting panel sheets, sewing cut panels with sleeves and packing finished mattress protectors in a presentable manner. These operations are convoluted and time consuming. Due to high market share, demand for products is very high; however, due to human error and a lack of efficiency, the manufacturer has struggled to meet market needs. Prior research was conducted to understand the manufacturers craft operations before implementing novel manufacturing methods. The time taken for multiple operations on the production line was recorded (e.g.: cutting, sewing, and folding operations). The following sections denote the stage-by-stage observations across the production line. Extensive time and human resources were devoted to understanding and capturing the different characters of mattress production. The traditional factory shopfloor consists of one cutting machine, six sewing stations, one folding and 12 packing stations. Work is conducted manually by hand, where work ability of each individual worker is highly variable, and the calculated mean performance is, therefore, not accurate.

### 3.3.1 Inventory

The first step of the field study was to simulate the inventory management and record the time required to arrange inventory items, such as raw materials for production, tags, labels, threads, and others. Table 3 lists the inventory timings of traditional and expected timings.

**Table 3 Traditional mattress protector simulations (e.g., median of protectors)**

| **Traditional practices** | **Simulated framework** | **SM** | **Expected median goal** |
|---|---|---|---|
| **20 min** | 10 min | | 15 min |

#### 3.3.1.1 Traditional Practices

Raw materials in inventory are handled manually. Human and manual machine resources (e.g., a pallet jack) are used to transport raw materials from the inventory to the cutting stations depending on the expected output. Similarly, finished goods are taken from the packing machine to the inventory and placed accordingly. For example, for a single mattress protector, textile is used. In the inventory, raw textile goods are sorted based on a manually performed scan, and the time needed to identify the location of the raw material, palletisation and depalletization is expected to be approximately 20 minutes for each pallet process.

#### 3.3.1.2 Smart Manufacturing Practices

The manual handling process of pallets is replaced by the use of automatic guided machines/human-defined paths so that resource follows the exact path and reaches the station on time. The in-bound process takes the raw materials from the inventory to the station, while the out-bound process carries finished goods to the storage systems. In the inventory, scanning and sorting technology along with storage location information can be retrieved from computer systems. Automation helps identify the exact location of the goods, saving time scanning additional goods. This was previously time consuming, as scans were performed using a trial-and-error method. Using an automatic storage and retrieval system can alter the time elapsed during the simulation depending on the specifications of the machinery installed. A reduction in time by half the initial value, which was approximately 10 minutes, was expected. The reasons for a reduction in time were auto limit detection at workstations, which facilitates the inventory process; product location detection; auto-palletisation and depalletization; transfer to workstations according to defined paths; and speed alteration depending on machine specification.

#### 3.3.1.3 Application

During the initial production line run, machinery is inspected, and, during a shift change, some delay is expected in the machinery, as well as during annual or quarterly maintenance. Inventory handling is conducted manually, and technical knowledge is needed to program advanced installed inventory, set the pace and meet market requirements. Slow-paced work is recommended until technical experience is acquired, with an expected timeframe of approximately 15 minutes.

### 3.3.2 Cutting Operation

The next step of the field study was the cutting operation. This operation includes the complex steps that occur before the start of production. Table 4 details traditional and simulated timings.

**Table 4 Cutting table observations**

| **Single** | | **Traditional time (sec)** | **Simulated time (sec)** |
|---|---|---|---|
| **7 pieces/roll** | Setup | 5 | 2 |
| | Process | 12 | 6 |
| | Teardown | 6 | 2 |
| **Queen** | Setup | 7 | 4 |
| **6** | Process | 14 | 8 |

| | | | |
|---|---|---|---|
| **pieces/roll** | Teardown | 8 | 4 |
| **Super king**<br><br>**5 pieces/roll** | Setup | 8 | 6 |
| | Process | 16 | 10 |
| | Teardown | 8 | 6 |
| **Utilisation** | | 40% | 65% |
| **Resources used** | | Human resource 1<br><br>Machine resource 1<br><br>Transporters 1 | |

### 3.3.2.1 Traditional Practices

At the cutting station, the production run is conducted manually. Raw materials are brought to and loaded onto the workstation by hand. Depending on the output, the required cuts are made manually. The cutting machine is human operated, and the cut pieces are transferred to other sewing stations operated by hand. The cut pieces are carried in random batches to random sewing machines depending on availability. This process is verified and error prone, and the actual mean performance of the workers is unknown. Cut pieces are carried from the cutting station to the sewing station depending on the availability of sewing machines, which is in turn dependent on human performance. Material transport human resources and human resources are used at workstations to control, load and unload the materials. Heavy workloads can increase the risk factor, and miscommunication can cause major distributions and delays. Many random variables have been considered approximate mean values of run time for products-mix outputs, such as singles and queens, based on calculations and performance values over the last six months for the cutting workstations.

The teardown time is almost equal to or slightly greater than that of the setup time. This is because a one-unit roll is cut into pieces that are arranged in a batch manner to be transferred to another workstation. The setup time for the cutting machine is 5, 7 and 9 seconds for a product mix of singles, queens and super kings, respectively. The teardown time tends to be higher than the setup time, and the estimated values are 6, 8 and 10 seconds. A total of 7, 6 and 5 cut pieces of single, queen and super king, respectively, are processed from an individual roll. Here, the processing time directly depends on he expected outputs. For example, the processing times for singles, queens and super kings are 12, 14 and 16 seconds. The machinery tends to stay idle during loading and, as the units are unloaded manually, the actual utilisation of machine is lower at only 40%.

#### 3.3.2.2 Smart Manufacturing Practices

Automation constrains the setup, processing and teardown time of workstations. The constrained value depends on the machine specification. Machines are semiautomated when humans control the run process of the workstation. The cutting process is automatic; as in the previous case, the machines are handles by humans when performing the cutting process, though resource involvement is linked with the setup and teardown time. The cutting speed and number of pieces is controlled by hand depending on product mix, though this can also be accomplished using computers in the control room with the aid of advanced DT technologies. The transportation channel is eton lines, which carry cut pieces from the cutting workstation to the sewing workstations. Cut units are directly picked onto eton lines and are auto-oriented, which removes the need for piling up the cut pieces into batches for the sewing workstations, as in the previous scenario. In a simulation run, the setup time is constrained to 2, 4 and 6 seconds for single, queen and super king product ranges, respectively. The decrease in time is due to the integration of inventory into the transportation of raw goods and palletisation/depalletization. Further, integrating the eton conveyor line decreases the teardown time of the cutting machine. However, the machine run process is linked with the specifications of the machine installed in the production line. Advance machinery offers the flexibility to alter the speed of the run and the number of units obtained. Simulation is estimated to run the process at a speed of 6 to 8 seconds, with a mean variation of 2 seconds between each product mix output. Constraining the production line during simulation to obtain optimal solutions gives an estimated utilisation value of the cutting machine of approximately 65%.

#### 3.3.2.3 Application

During the implementation phase, the skill of the worker is assessed, and their technical ability with machinery is important to ensuring the seamless running of the production line. When new machinery installed, it is recommended that the initial pace is set at optimal run values. These values can subsequently be reduced with extra care taken to maximise production. Here, the workstation was semiautomatic. The setup and teardown tended to have higher values than the simulation setup time values of 3, 5 and 7 seconds and the teardown time values of 4, 6 and 8 seconds for the product-mix scenario. Considering the initial optimal pace of work environment, the processing vales were 8, 10 and 12 seconds for single, queen and super king batches. But human and machine resource involvement made the production line semi-automated, and the dynamic nature of these resources affected the setup and teardown time of workstations such that the utilisation rate was 55%.

### 3.3.3 Sewing Operation

Table 5 depicts the sewing operation timings observed during the field study and the steps involved in the sewing operation. This is the third step in the process of manufacturing mattress protectors.

**Table 5 Sewing station timings**

| **Single** | | **Traditional time (seconds)** | **Simulated time (seconds)** |
|---|---|---|---|
| | Setup | 8 | 5 |
| | Process | 60 | 50 |
| | Teardown | 8 | 5 |
| **Queen** | Setup | 8 | 5 |

| | | | |
|---|---|---|---|
| | Process | 60 | 50 |
| | Teardown | 8 | 5 |
| **Super king** | Setup | 8 | 5 |
| | Process | 60 | 50 |
| | Teardown | 8 | 5 |
| **Utilisation** | | 40% | 60% |
| **Resources used** | | Human resource 6<br>Machine resource 6<br>Transporters 4 | |

### 3.3.3.1 Traditional Practices

At the sewing station, the production run is performed manually. The batch products are transferred from the cutting machine to the sewing machines using dynamic pathways. A human agent transports items between workstations and carries the batch products. Sewing is performed manually using a machine to stitch the products. Time and performance factors are dynamic and independent. The ability to work with increased demand flexibility is not afforded by this environment. The sewing operation is the core process of the production line, and the product-mix batches also affect the work pace. Differential mean values are considered for the product-mix setup. The setup and teardown times are considerably higher than those of the cutting workstation. This is due to an exchange of products between transporters and human resources at the workstations and the output acknowledgment of each batch before undergoing sewing. In the case study, six sewing workstations were installed on the factory floor. Though human involvement has a dynamic nature, the mean of recorded six months value is thought to determine the current performance level of an industry 2.0 production line. In the example, the approximate setup and teardown times were 8 seconds for the product-mix scenario. Manual sewing is a time-consuming process in which standards are followed, and the ability to switch between product-mix scenarios is challenging; however, despite the dynamic nature of sewing implementations, the average value was considered for all batch operations, and the sewing process was thought to be performed at a rate of 60 seconds. The sewing process was ideal during loading and unloading the units manually. Therefore, the actual utilisation rate of a machine was lower at only 40%.

#### 3.3.3.2 Smart Manufacturing Practices

Similar to the cutting workstation, the simulation constrains the setup, processing and teardown time of workstations. The constrained value depends on machine specifications. A machine is semiautomated when the run (process) of the workstation is controlled by hand. In the case study, the sewing process was automatic, as the machine that performed the sewing operation was operated by hand. Here, human resource involvement was linked with the setup and teardown times. The run (process) involvement included altering the sewing speed and the expected output batch, depending on the product mix. This could also be achieved using computers in the control room with the help of advance DT technologies. The transportation channel used eton lines to carry cut pieces from the cutting workstation to the sewing workstations. Here, the sewing units are directly picked and placed onto eton lines when once processed in the sewing workstation. In the simulation run, the setup time was constrained to 5 seconds for all batches. This decrease in time stemmed from the integration of inventory into the transportation of raw goods, palletisation and depalletization. Integrating eton lines decreased the teardown time of the sewing machine to 5 seconds. However, the machine run (process) was linked with the specifications of the machine installed in the production line. Advanced machinery provides the flexibility to alter the speed of the run and the number of units obtained. The simulation estimated the run process at an average speed of 50 seconds for all product-mix outputs. Constraining the production line during the simulation to obtain optimal solutions gave an estimated utilisation rate for individual sewing machines of 8% to 10%; however, when considered collectively, the rate was 60%.

#### 3.3.3.3 Application

During the installation phase, a worker 's skills are evaluated. Their technological proficiency with the machinery plays an important role in the smooth running of the production line. For the newly installed machinery, the initial pace was set at optimum running values. Throughout the cycle, lower time values could be adjusted, taking extra care to optimise production. Here, the workstation was semi-automatic, and the setup and teardown times appeared to be higher than the time taken in the simulation values (6 seconds) and processing time (55 seconds) for the product-mix scenario. The presence of human and machinery resources renders the line semi-automated, and the complex design of these resources affects the setup and time of teardowns. The utilisation rate of individual sewing machine was approximately 8% to 9%, and collectively the rate was 50%.

### 3.3.4 Folding Operation

The next important step in the process of mattress protector manufacturing is folding. This operation involves complex materials and requires folding to precise sizes so that goods can fit into pre-made packaging. Table 6 lists the timings noted during the folding operation.

**Table 6 Folding machine timings**

| | | **Traditional time (sec)** | **Simulated time (sec)** |
|---|---|---|---|
| **Single** | Setup | 8 | 5 |
| | Process | 14 | 7.5 |
| | Teardown | 10 | 6 |
| **Queen** | Setup | 8 | 5 |
| | Process | 15 | 7.5 |
| | Teardown | 10 | 6 |
| **Super king** | Setup | 8 | 5 |
| | Process | 16 | 7.5 |
| | Teardown | 10 | 6 |
| **Utilisation** | | 40% | 60% |
| **Resources used** | | Human resource 1<br>Machine resource 1 | |

| |
|---|
| Transporters 2 |

#### 3.3.4.1 Traditional Practices

From the sewing stations, products are then transferred to folding stations. In the case study, this was performed manually by humans who transported the items to the folding stations. Two human transporters carried the sewn products to the folding stations. From there, they were sent to packaging stations. Packing was also performed manually. As this step deals with large textiles, handling the operations is challenging. As a result, the time taken for setup and teardown was comparatively higher than all other workstations. The setup time and teardown time for the folding stations was 8 seconds and 10 seconds, respectively, for all product-mix scenarios. The processing time was approximately 10 seconds for all batch processing. The utilisation rate of a folding machine was 40%.

#### 3.3.4.2 Smart Manufacturing Practices

Virtual simulation helped model and render the folding workstation outputs; however, the large size ratio was easier to handle in the virtual world than the physical world. Time considerations were according to practical implication. Optimistic values were considered. The setup time and teardown times had a slight variation of 1 second, the teardown time being the higher value, with 6 seconds for product mix batches. The processing time for the folding process was 7.5 seconds. The optimal utilisation of the workstation was 60%.

#### 3.3.4.3 Application

During the implementation phase, uncertainties play a vital role and deviate the goal of optimal solutions. Deviation was examined over a period. The folding machine had mid values between the industry 2.0 production line and the simulation production line. The setup time and teardown times for the folding stations were 7 seconds and 8 seconds, respectively. The processing time for this component was 10 seconds. Utilisation was altered over market demand, but the initial considerations had a value of 50% under the normal work pace.

### 3.3.5 Overall Time Difference

Table 7 depicts the total time difference observed during the manufacture of a bulk order of mattress protectors. Average timings were calculated for individual products and are presented in Table 7.

**Table 7 Time difference noted**

| | Traditional time (sec) | Simulation time (sec) |
|---|---|---|
| **Single** | 131 | 88.5 |
| **Queen** | 138 | 94.5 |
| **Super king** | 142 | 96.3 |

### 3.3.5.1 Traditional Practices

The overall timeframe of the production line was calculated, including the workstation setup and processing and teardown timings. The maximum values of the timeframe were obtained for the current industry 2.0 production line. The values of the product mix for single, queen and super king mattress protectors were 131 seconds, 138 seconds and 142 seconds, respectively.

### 3.3.5.2 Smart Manufacturing Practices

The virtual simulation considered constrained values in many scenarios. Some of these variables fell in a controllable category and some did not fall in the controllable category. These independent uncontrollable variables influenced the project implementation phase. The results obtained in the virtual simulation were the optimal solution an individual could derive from the production line. Experimental scenarios were easy to perform, and solutions were obtained rapidly. During the experimental simulation, the values obtained were 88.5 seconds, 94.5 seconds and 98.5 seconds for single, queen and super king batches, respectively.

### 3.3.5.3 Expected Timings

During the implementation phase, the production line suffers from several uncertainties that minimise and nullify over several months when risk, optimal and feasible studies are regularly conducted and implemented. Thus, optimal solutions tend to be obtained from the simulation model. The graph produces follows a parallel path to the graph modelled accounting for the simulation results. For the initial slow-paced considerations, the timings for single, queen and super king batches were 103 seconds, 113 seconds and 119 seconds, respectively.

## 3.3.6 Operator Efficiencies

Table 8 readings were observed when operators loaded and unloaded various machinery. These timings were critical to ascertain efficiency. The readings were converted into an efficiency percentage to gauge the operators' performance.

**Table 8 Operator simulation**

| Utilisation | Traditional time | Simulated time | Expected time |
|---|---|---|---|
| | 70% | 85% | 80% |

### 3.3.6.1 Traditional Practices

Worker tasks include loading and unloading the stations, transferring products between different sequential workstations and engaging in inventory management using machine resources. The pathways followed and their independent efficiency values are dynamic; therefore, usually, in complex scenarios, resources are not used to their maximum values. In the case study, the utilisation rate of human resources was 70%.

### 3.3.6.2 Smart Manufacturing Timings

The simulation involved considering 60% as moderate efficiency of operators. The values considered in the simulation run were fixed and could be altered but affected the complete production line. Therefore, research was conducted with technical staff to identify the optimal performance values. The remaining tasks were conducted as part of the automation using integrated advance machines. Defining the pathways constrain also gave the optimal values for human resource utilisation. In the simulation, the human resource utilisation rate obtained was 85%.

### 3.3.6.3 Expected Timings

Human health, a lack of familiarity of the production environment, a lack of product and technical knowledge, long shifts, heavy workloads, dynamic working environments, human behaviour, breaks and safety issues are some key considerations that can affect the production run. Humans tend to exhibit dynamic behaviours; therefore, working at the same pace as in the simulation model was impractical. However, with regular training, health check-ups, and performance meetings with operators, the efficiency to required level seemed achievable. These can help an individual to focus and can enhance the input ability so that the utilisation can be estimated at approximately 80%.

## 3.3.7 Output Units

Table 9 represents the total production recorded on a typical busy production day. The readings were matched with the monthly production average. Three timings illustrated in this table identified the output differences. The difference production was targeted from the production.

**Table 9 Product outputs per day**

| | **Traditional time** | **Simulated time** | **Expected time** |
|---|---|---|---|
| **Single** | 800–1000 | 1200–1400 | 1000–1200 |
| **Queen** | 200–300 | 350–450 | 300–400 |
| **Super king** | 150–250 | 200–400 | 150–350 |

### 3.3.7.1 Traditional Practices

The existing production line output was 800–1,000 units of singles, 200–300 units of queens and 150–250 units of super kings. As the market demand was dynamic, there was no flexibility to adjust the production line to meet market demand, as the industrial process involved a cluster of processes that had to be altered, such as scheduling, analysis, run setup, maintenance setup, staffing, safety issues, technical factors, machine constraints and integration constraints.

### 3.3.7.2 Smart Manufacturing Practices

During the virtual simulation, advanced machinery was installed, such as computer-aided design modelled components. They were considered in virtual environments. The process constraints (e.g., time, schedule, pathways, process sequence) were used to run experimental scenarios. For the experimental simulation in the virtual world, the obtained values were 1200–1400 units for singles, 350–450 for queens and 200–400 for super kings.

#### 3.3.7.3 Expected Timings

During the implementation phase, regular machine check-ups were performed before and after every production run. Mechanical loses during the run, technical knowledge, independent pathway travels, loss of connectivity, system failures, logistics delays and environmental factors, as well as other controllable and uncontrollable considerations, can affect the production run. Here, the estimated output values were 1,000–1,200 units of singles, 300–400 units of queens and 150–350 units of super kings.

After modelling in Simio, it was set to run, and animation of the software provided an overall perspective of the sequential process of the production line. This line assisted in training the model sets with different entities. The labels marked at each workstation provided real-time data on the ongoing application count after each order was processed in the overall estimation of the application model from each station to verify the simulation model fluency. As shown in Tables 10 and 11, this process led to a data comparison between the theoretical and practical simulation results that helped gather process and station data. The same data are graphically depicted in Figures 13 and 14. The total individual time taken by each station in the bottom row of each entity process in Table 10 and the total individual subset process time (setup, processing time, teardown time) was calculated. The time taken at each station was calculated according to the amount of time the station was in use. The total time taken for the process was then calculated by dividing the total machine time with total number of the station and then multiplied with overall shift time. This resulted in the actual utilisation ratio of the total time required by a machine. The time required by each machine per day was multiplied by the number of units available. Thus, the operation had to align with the utilisation reading that were not more than 100.

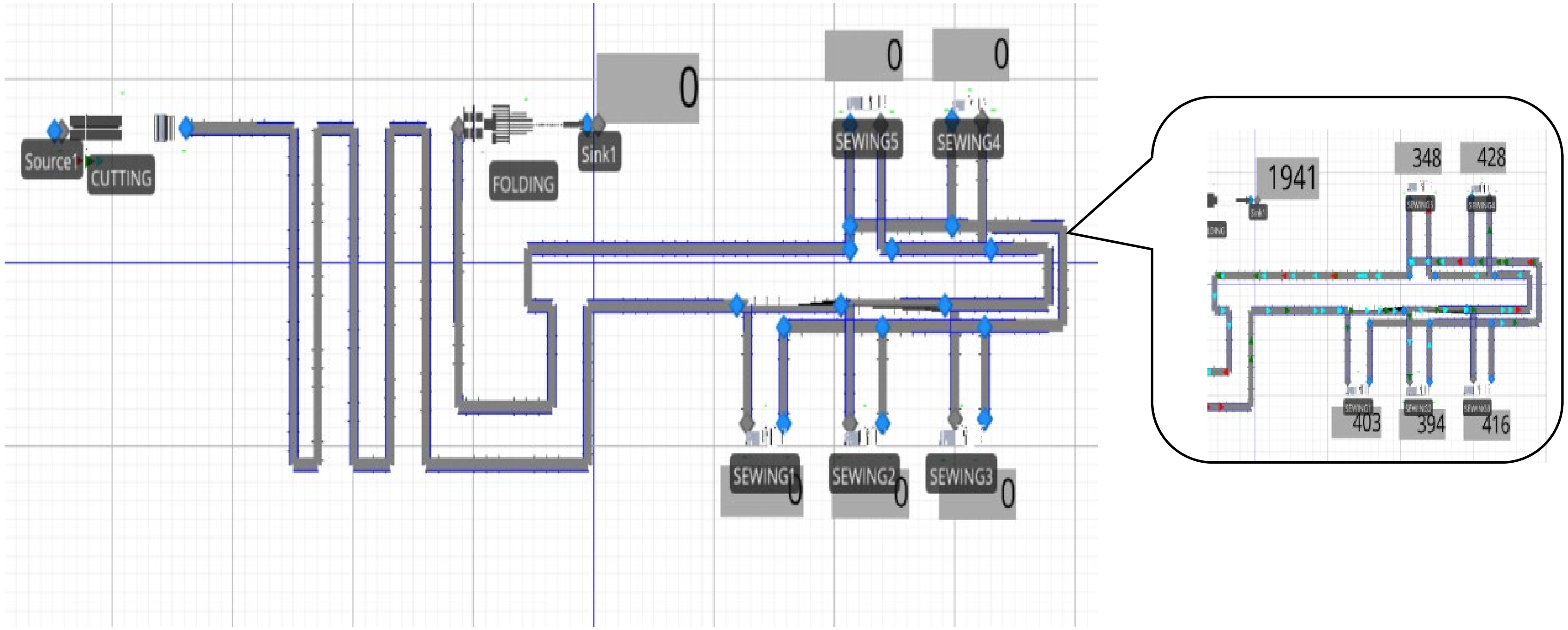


**Figure 12 Warehouse optimisation and simulation**

**Table 10 Practical process timings**

| Product type | Process | 1 | 2 | 3 | 4 | 5 | Total | Output/day (Units/ day) | Mix |
|---|---|---|---|---|---|---|---|---|---|
| Single | Station | Cutting | Moving | Sewing | Moving | Folding | | 1300 | 65 |
| | Setup | 1.4 | 0 | 5 | 0 | 5 | 11.4 | | |
| | Process | 6 | 0 | 50 | 0 | 7.5 | 63.5 | | |
| | Teardown | 0 | 0 | 5 | 0 | 3 | 8 | | |
| | | 7.4 | 0 | 60 | 0 | 15.5 | 82.9 | | |
| | | | | | | | | | |
| Queen | Station | Cutting | Moving | Sewing | Moving | Folding | | 400 | 25 |
| | Setup | 1.4 | 0 | 5 | 0 | 5 | 11.4 | | |
| | Process | 6 | 0 | 50 | 0 | 7.5 | 63.5 | | |
| | Teardown | 0 | 0 | 5 | 0 | 3 | 8 | | |
| | | 7.4 | 0 | 60 | 0 | 15.5 | 82.9 | | |
| | | | | | | | | | |
| Super King | Station | Cutting | Moving | Sewing | Moving | Folding | | 300 | 15 |
| | Setup | 3.75 | 0 | 5 | 0 | 5 | 13.75 | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Process** | **7.5** | **0** | **50** | **0** | **8.5** | **66** |
| **Teardown** | **0** | **0** | **5** | **0** | **3** | **8** |
| | **11.25** | **0** | **60** | **0** | **16.5** | **87.75** |

**Table 11 Simulated readings from line balancing the production line**

| Workstation | Expected utilisation | Software simulated readings |
|---|---|---|
| **Cutting** | 63% | 62.93% |
| **5 Sewing machines** | 64% | 62.51% |
| **Folding** | 63% | 62.81% |
| **Expected output per day** | | Obtained output using simio sequence |
| **2,000 units** | | 1941 units |

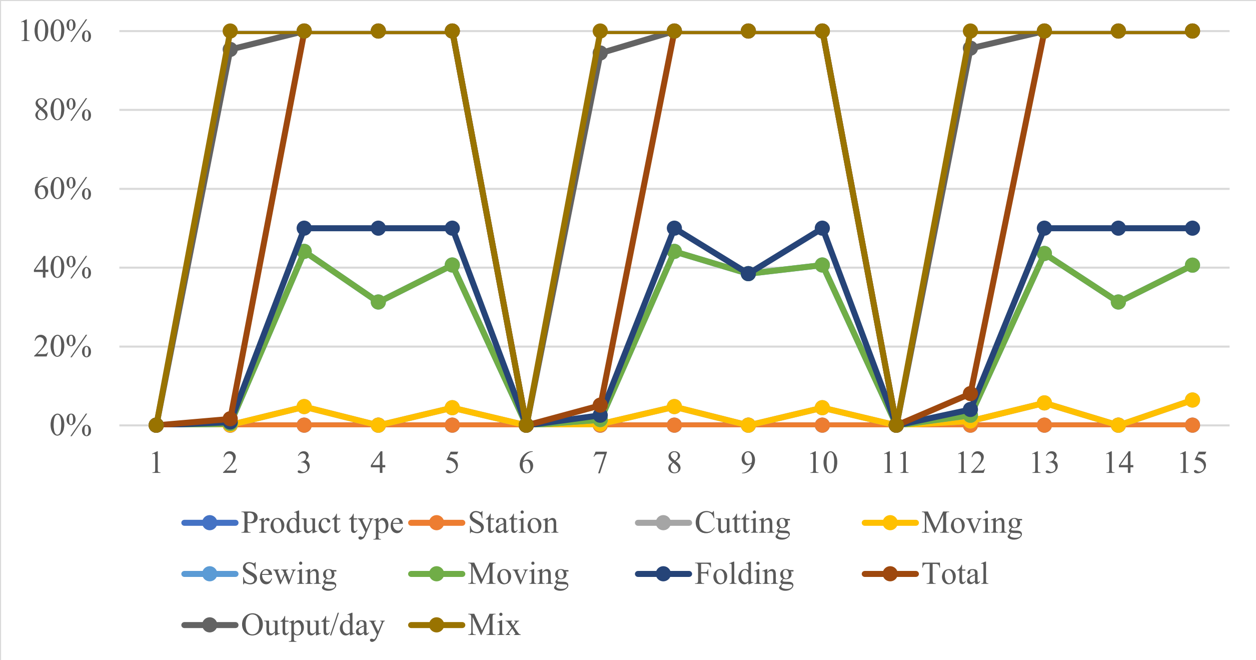


**Figure 13 Production analytics**

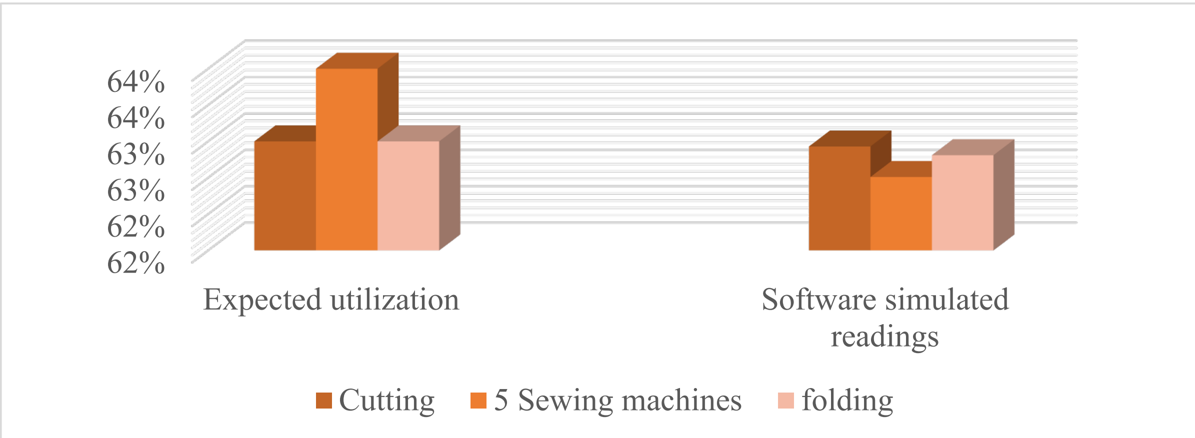


**Figure 14 Line balancing production outcomes**

This research proposed a potential cloud robotics framework that can be used for smart city applications. Through task offloading for a robotic-aided operation control system, this research presented an optimisation problem for an analogical algorithm. Following this, an SM-based scheme was established to identify the optimal offloading decisions while meeting the system constraints. The results demonstrated the advantage of ongoing ML algorithms over other benchmarks (i.e., near-optimal results with fewer overheads), as well as its adaptability in a changing environment (e.g., a change in bandwidth and movement). It also helped identify the benefits and shortcomings of ML for the given scenario and pinpoint scope for further improvement. Based on these results, the robot path planning (movement) and network connectivity/availability could be integrated to the optimisation problem in future work to further enhance the system performance. In addition, the present research also sought to run tests on a practical system to achieve similar results to the theoretical system.

## 3.4 Cost and Takt Analysis

Cost analysis is a systematic approach towards estimating the strengths and weaknesses of certain approaches to identify which course of action will yield the best results for the least expense. Cost analyses can be used to compare completed or potential courses of actions or estimate (or evaluate) the value against the cost of a decision, project or policy. Cost analyses are commonly used in commercial transactions, business policy decisions and project investments.

There are two main applications of cost analyses. The first is to determine whether an investment is sound according to whether—and by how much—its benefits outweigh its costs. The second is to provide a basis for comparing investments (by comparing the total expected cost of an option with its total expected benefits).

The process of conducting a cost analysis has the following steps:

i) The goals and objectives of the action are defined.
ii) Alternative actions are listed.
iii) Measurements are selected, and cost and benefits elements are measured.
iv) Outcomes, cost and benefits are predicted over the relevant time.
v) Costs and benefits are converted into a common currency.
vi) A discount rate is applied.
vii) The next present value of actions under consideration is calculated.
viii) A performance sensitivity analysis is conducted.
ix) The recommended course of action is adopted.

The takt time is the average time between the start of production of one unit and the start of production of the next unit when the production starts are set to match the rate of customer demand. For example, in the present research, an order number of 25 3013F3XL from the Buddies range was taken. For this order, given a 40-hour work week and steady flow through the production line, the average time between production starts should be 8.2 hours (or less than this to account for circumstances such as machine downtime and scheduled paid employee breaks). The takt time simply reflects the rate of production needed to match demand. In the previous example, regardless of whether it takes four minutes or four years to produce a product, the takt time is based on customer demand. If a process or production line cannot complete production within the takt time, either demand levelling, additional resources, or process reengineering is needed to correct the issue.

Time analysis is a sequence of defined data points measured at different time intervals over a period. For example, in the present research, four different kinds of product from the Buddies range were selected, and the laying time, cutting time, quilting time, sewing time and packaging time were calculated. Tables 12, 13 and 14 provide detailed information on how the time needed for the different stages of production was calculated. A time analysis was also conducted and included the lead time, which is the time between when an order comes into the factory and the day it is delivered to the customer.

**Table 12 Time and cost analysis of mattress protectors[1]**

| Product | Signature Tencel Mattress Protector | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Fabric** | | Tencel Elite | | | | | | | | | | |
| | | | | | **Manual** | | | | **Semi-automated** | | | |
| **Material** | | Item No | Unit | Cost | LSG* | KNG* | LSG* | KNG* | LSG | KNG | LSG | KNG |
| **Panel** | Fabric Top | 1002051 | Mtr | $4.01 | 0.96 | 1.89 | $3.85 | $7.59 | 0.96 | 1.89 | $3.85 | $7.59 |
| | Fabric Bottom | | Mtr | | | | $0.00 | $0.00 | | | $0.00 | $0.00 |
| **Skirt** | Fabric Std | 1002040 | cm | $2.06 | 6.12 | 7.98 | $12.62 | $16.46 | 6.12 | 7.98 | $12.62 | $16.46 |
| | Fabric XD | | Mtr | | | | $0.00 | $0.00 | | | $0.00 | $0.00 |
| | Elastic | | Mtr | $0.07 | | 5.6 | $0.00 | $0.39 | | 5.6 | $0.00 | $0.39 |
| **Label** | C&C | | Ea. | $0.05 | 1 | 1 | $0.05 | $0.05 | 1 | 1 | $0.05 | $0.05 |
| | Woven | | Ea. | $0.09 | 1 | 1 | $0.09 | $0.09 | 1 | 1 | $0.09 | $0.09 |
| **Other** | Binding | | Mtr | | | | $0.00 | $0.00 | | | $0.00 | $0.00 |
| **Packaging** | Bag | 1008016 | Ea. | $0.47 | 1 | | $0.47 | $0.00 | 1 | | $0.47 | $0.00 |
| | | 1008017 | Ea. | $0.50 | | 1 | $0.00 | $0.50 | | 1 | $0.00 | $0.50 |
| | | 1008005 | Ea. | $0.39 | | | $0.00 | $0.00 | | | $0.00 | $0.00 |
| | Box | | Ea. | | | | $0.00 | $0.00 | | | $0.00 | $0.00 |
| | Outer Carton | | Ea. | | 0.05 | 0.08 | $0.05 | $0.08 | 0.05 | 0.08 | $0.05 | $0.08 |
| | Pack Board | 1008063 | Ea. | $0.20 | 1 | | $0.20 | $0.00 | 1 | | $0.20 | $0.00 |
| | | 1008061 | Ea. | $0.22 | | 1 | $0.00 | $0.22 | | 1 | $0.00 | $0.22 |
| | | 1008064 | Ea. | $0.20 | | | $0.00 | $0.00 | | | $0.00 | $0.00 |
| | Insert | | Ea. | $0.48 | 1 | 1 | $0.48 | $0.48 | 1 | 1 | $0.48 | $0.48 |
| | Guarantee Card | PAB512 | Ea. | $0.04 | 1 | 1 | $0.04 | $0.04 | 1 | 1 | $0.04 | $0.04 |
| | Brochure | | Ea. | | 1 | 1 | $0.00 | $0.00 | 1 | 1 | $0.00 | $0.00 |
| | Gross material cost | | | | | | $17.85 | $25.89 | | | $17.85 | $25.89 |
| **Labour** | | | | | | | | | | | | |
| **Cutting** | Panel | | Sec | $0.012 | 45 | 45 | $0.56 | $0.56 | 25 | 25 | $0.31 | $0.31 |
| | Skirt | | Sec | $0.012 | 45 | 45 | $0.56 | $0.56 | 25 | 25 | $0.31 | $0.31 |
| **Sewing** | | | Outsourced | | | | $1.60 | $1.80 | | | $1.60 | $1.80 |
| **CMT** | Line feeding | | Sec | $0.01 | $60.00 | $60.00 | $0.63 | $0.63 | $30.00 | $30.00 | $0.32 | $0.32 |
| | Packing | | Sec | $0.01 | $96.00 | $114.00 | $1.01 | $1.20 | $96.00 | $114.0 | $1.01 | $1.20 |
| | Gross labour cost | | | | | | $3.80 | $4.19 | | | $3.24 | $3.62 |
| | Gross cost | | | | | | $21.65 | $30.08 | | | $21.09 | $29.52 |
| | Mfg. Overhead | | 17% | | | | $3.68 | $5.11 | | | $3.59 | $5.02 |

* LSG – Long single, KNG- King single, ea-each, Mtr-metre

| | | | | | | |
|---|---|---|---|---|---|---|
| Total manufacturing | | | $25.34 | $35.20 | $24.67 | $34.54 |
| Invoice price | | | $45.00 | $80.00 | $45.00 | $80.00 |
| Rebate | | | $0.00 | $0.00 | $0.00 | $0.00 |
| Nett selling price | | | $45.00 | $80.00 | $45.00 | $80.00 |
| Gross margin | | | $19.66 | $44.80 | $20.33 | $45.46 |
| Gross margin % | | | $0.44 | $0.56 | $0.45 | $0.57 |
| Retail price | Mark Up | 100% | $90.00 | $160.00 | $90.00 | $160.00 |
| RRP less GST | | 10% | $81.82 | $145.45 | $81.82 | $145.45 |
| Retail GP | | | $36.82 | $65.45 | $36.82 | $65.45 |
| Retail GP% | | | $0.45 | $0.45 | $0.45 | $0.45 |

**Table 13 Cost and time analysis (Chair pad 1021)**

| **Product** | **BD1021N** | **Chair Pad 50x60cm - Navy** | | | | **Name:1021N** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Code** | Description | Old Costings | | | | New Costings in-house quilting | | | | | New Costings Pre-Quilted | | | |
| | | Staff | Usage | Unit Cost | Sub Total | Staff | Usage | Units | Unit Cost | Sub Total | Staff | Usage | Unit Cost | Sub Total |
| **1002057** | Felt 400 gsm fabric | | 0.3 | $2.37 | $0.71 | | 0.3 | Mtr | $2.37 | $0.71 | 5.45 | | | |
| **1002059** | Navy Interlock Fabric | | 0.03 | $2.75 | $0.08 | | 0.03 | Mtr | $2.75 | $0.08 | | | | |
| **1006002** | Labour - Laying / Cutting | 2 | 1.5 | $1.83 | $2.74 | 1 | 240 | Seconds | $1.05 | $2.52 | | | | |
| **1002008** | Duraflex White Waterproof Fabric | | 0.17 | $6.15 | $1.04 | | 0.17 | Mtr | $6.15 | $1.04 | | 0.17 | $6.15 | $1.04 |
| **1005000** | Buddies Printed Care Label | | 1 | $0.05 | $0.05 | | 1 | Qty | $0.05 | $0.05 | | 1 | $0.05 | $0.05 |
| **1006001** | Labour - Sewing | 1 | 1.9 | $0.56 | $1.06 | 1 | 300 | Sec | $1.05 | $3.15 | 1 | 300 | $1.05 | $3.15 |
| **1006000** | Labour - Packing | 1 | 1.5 | $0.42 | $0.63 | 1 | 80 | Sec | $1.05 | $0.84 | 1 | 80 | $1.05 | $0.84 |
| **1008005** | Bag | | 1 | $0.10 | $0.10 | | 1 | Qty | $0.10 | $0.10 | | 1 | $0.10 | $0.10 |
| | Insert | | 1 | $0.10 | $0.10 | | 1 | Qty | $0.10 | $0.10 | | 1 | $0.1 | $0.10 |
| | | | | | | | | | | Total | $6.52 | | | |
| | Gross cost | | | | $6.52 | | | | | $8.60 | | | | $10.74 |
| | Mfg. Overhead | | 17% | | $1.11 | | | | | $1.46 | | | | $1.83 |
| | Total manufacturing | | | | $7.63 | | | | | $10.06 | | | | $12.57 |
| | Invoice price | | | | $15.00 | | | | | $15.00 | | | | $15.0 |
| | Rebate | | | | $0.00 | | | | | $0.00 | | | | $0.00 |
| | Nett selling price | | | | $15.00 | | | | | $15.00 | | | | $15.0 |
| | Gross margin | | | | $7.37 | | | | | $4.94 | | | | $2.43 |
| | Gross margin % | | | | 49% | | | | | 33% | | | | 16% |
| | Retail price | Mark Up | 100% | | $26.95 | | | | | $26.95 | | | | $26.9 |
| | RRP less GST | | 10% | | 24.5 | | | | | 24.5 | | | | 24.5 |
| | Retail GP | | | | $9.50 | | | | | $9.50 | | | | $9.50 |
| | Retail GP% | | | | 38.78% | | | | | 38.78% | | | | 38.78% |

**Table 14 Cost and time analysis (1070K bed pad)**

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **PRODUCT** | **1070K** | **Lite N Easy Bed Pad White** | | | | | | | | | | | | |
| **NAME:** | 1070K | | | | | | | | | | | | | |
| **Code** | Description | Old Costings | | | | **"New Costings in-house quilting"** | | | | | **"New Costings Pre-Quilted"** | | | |
| | | Staff | Usage | Unit Cost | Sub Total | Staff | Usage | Units | Unit Cost | Sub Total | Staff | Usage | Unit Cost | **Sub Total** |
| **1002056** | Felt 230gsm Fabric | | 1.835 | $1.27 | $2.33 | | 1.835 | Mtr | $1.27 | $2.33 | | | 3.76 | |
| **1002019** | Tricot White Polycotton Fabric | | 1.835 | $0.77 | $1.41 | | 1.835 | Mtr | $0.77 | $1.41 | | | | |
| **1006002** | Labour - Laying / Cutting | 2 | 1.5 | $1.83 | $2.74 | 1 | 300 | Seconds | $1.05 | $3.15 | | | | |
| **1005000** | Buddies Printed Care Label | | 1 | $0.05 | $0.05 | | 1 | Mtr | $0.05 | $0.05 | | 1 | $0.05 | $0.05 |
| **1002008** | Duraflex White Waterproof Fabric | | 1.835 | $6.15 | $11.28 | | 1.835 | Qty | $6.15 | $11.28 | | 1.835 | $6.15 | $11.28 |
| **1006001** | Labour - Sewing | 1 | 4.9 | $0.56 | $2.74 | 1 | 360 | Seconds | $1.05 | $3.78 | 1 | 360 | $1.05 | $3.78 |
| **1006000** | Labour - Packing | 1 | 1.5 | $0.42 | $0.63 | 1 | 80 | Seconds | $1.05 | $0.84 | 1 | 80 | $1.05 | $0.84 |
| **1008031** | Bag | | 1 | $0.10 | $0.10 | | 1 | Qty | $0.10 | $0.10 | | 1 | $0.10 | $0.10 |
| | Insert | | 1 | $0.10 | $0.10 | | 1 | Qty | $0.10 | $0.10 | | 1 | $0.10 | $0.10 |
| | | | | | | | | | | Total | | $21.38 | | |
| | Gross cost | | | | $21.38 | | | | | $23.05 | | | | **$19.91** |
| | Manufacturing overhead | | 17% | | $3.63 | | | | | $3.92 | | | | **$3.38** |
| | Total manufacturing | | | | $25.01 | | | | | $26.97 | | | | **$23.29** |
| | Invoice price | | | | $41.17 | | | | | $41.17 | | | | $41.17 |
| | Rebate | | | | $0.00 | | | | | $0.00 | | | | $0.00 |
| | Nett selling price | | | | $41.17 | | | | | $41.17 | | | | $41.17 |
| | Gross margin | | | | $16.16 | | | | | $14.20 | | | | $17.88 |
| | Gross margin % | | | | 39% | | | | | 34% | | | | 43% |
| | Retail price | Mark Up | 100% | | $71.95 | | | | | $71.95 | | | | $71.95 |
| | RRP less GST | | 10% | | 65.409 | | | | | 65.409 | | | | 65.4090 |
| | Retail GP | | | | $24.24 | | | | | $24.24 | | | | $24.24 |
| | Retail GP% | | | | 37.06% | | | | | 37.06% | | | | 37.06% |

## 3.5 Chapter Summary

In this chapter, a traditional manufacturing framework was analysed using a case study. The textile industry was chosen because it suffers from heterogenous disconnected complex operations, a lack of decision-making due to miscommunication in manufacturing and other disciplines and product variation demands due to personalisation. This chapter describes the field studies conducted in relation to a textile manufacturing company to analyse inefficiencies, current decision-making practices and manufacturing agility for low-volume personalised products. The following key points relating to the SM framework were derived:

i) With the target of efficient manufacturing, the proposed approach would make mattress production much more productive, time efficient and economically viable. Beyond the practical execution, future attempts should focus on integrating DT in real time. Integrating PS and VS would also make SM fully automated and more efficient, which should be the focus of the future studies. The initial implementation of the conceptual SM framework aimed to introduce real-time computing and the DT framework. This framework consisted of the actual implementation of operational layouts encapsulating heterogeneous characters for real-time computing.

ii) The SM conceptual framework considered many technologies and key components with a data-driven approach during development. The concept merged the virtual and physical shopfloors with data via a cloud platform. This provided seamless data integration and communication advantages, enhancing decision-making capabilities. The operations included a cradle-to-cradle approach, including pre-production, production, packaging and beyond. This data analysis provided seamless capabilities for future predictions based on past expedition. The characterisation of expedited data and predictive data mainly focused on addressing the type of classifiers and regression models that must be implemented in a real-world SM framework.

iii) The approach was practical and industry oriented, which demonstrated its viability. A conceptual framework of real-time computing using the advancements of the DT model was devised. ML algorithms were explored extensively to measure the verticals and horizontal applications across the manufacturing. Lastly, the practical implementation of the data accumulation setup was discussed, with a step-wise explanation for future reference.

iv) A case study was conducted within the textile industry, as this industry is multidisciplinary and inefficient, with disconnected operations, and requires large ranges of variants with low-volume manufacturing. The findings showed that an absorbent time was required for various products using traditional manufacturing (e.g., 158 seconds for a single mattress protector, 165 seconds for a queen mattress protector , and 180 seconds for a super king mattress protector). The exponential increase in the manufacturing time was mainly due to disintegrated operations and the lack of a balanced layout. In addition, the MES and ERP disconnect resulted in miscommunication, which resulted in poor decision-making. Further, the requirement for different variants and personalisation led to the need for a large inventory and extended setup times, which added to the complexity.

v) Field studies were conducted on various operations within textile manufacturing. Initially, the takt for various operations was recorded (e.g., videos of operating procedures and photographs of different phases). The cutting, sewing, folding and packing operations were studied. An increased disconnect in the various operations was observed, and the imbalanced manufacturing operations led to increased takt times. Inefficiencies in manufacturing operations were also observed due to disconnected MES. These inefficiencies included mechanical and sensory faults within the machinery; the requirement for manual reinforcements and replenishments during batch production, which resulted in increased setup times; and changes to design patterns, thread tensions and fabric type variations, which also increased setup times. Further, a lack of communication between disciplines (e.g., design space, purchase, shopfloor) was observed. This resulted in increased idle times and setup times due to a lack of decision-making. Operator setup times were also increased due to demands for personalised low-volume product manufacturing. This also led to the need for large inventories and created significant waste.

vi) A benchmarking study was simulated based on datasets obtained from catalogues of smart machineries (e.g., OEM data). This study was conducted for the multiple aforementioned operations. The takt times for the traditional versus simulated scenarios for the same set of operations were compared.

Heterogenous manufacturing operations were modelled using simulation software Simio. The benchmarking study indicated an increase of five minutes in the simulated study compared with the traditional initial setup time of 10 minutes. This increase was attributable to the planning and future proofing stock inventory analysis required for the shift. Compared with traditional methods, the simulated method led to enhanced efficiencies: 25% greater efficiency in the cutting and sewing operations and 20% increased efficiency in the folding operation. Folding and packing inefficiencies mainly resulted from customer demands for personalised packaging. The aforementioned increase in efficiency in the simulation stemmed from the removal of the setup and idle times required in traditional practice. Further, this analysis balanced the manufacturing line by optimally distributing operators on relevant operations.

vii) Takt studies were conducted on benchmarking traditional practices on different mattress protectors in the textile industry, and the results showed a substantial reduction in the time taken to manufacture the mattress protectors. For example, the manufacturing time for single mattress protectors reduced from 131 seconds to 88.5 seconds, for queen mattress protectors from 138 seconds to 94.5 and for super king protectors from 142 seconds to 96.3 seconds.

viii) The simulation also enhanced efficient line balancing, which allowed for efficient operational sequencing and operator movements and avoided operator inefficiencies, specifically through minimising idle time and enhancing communication and decision-making. Operator efficiencies were substantially enhanced. For example, there was a 15% efficiency increase in the simulation compared with 70% in traditional practice. The number of products produced per day was compared between the simulated and traditional manufacturing. The results showed a substantial increase in the number of products produced in a shift. The number of single mattress protectors produced increased from 900 to 1,300, queen mattress protectors from 250 to 400 and super king mattress protectors from 200 to 300.

In the following chapter, the SM framework components are discussed.

# 4 Smart Manufacturing Framework

This chapter frames a novel SM framework. This novel framework is considered with all possible expected machinery, software implementations, ML implementation and possible integration with ERP and MES. This framework was developed for a general manufacturing company. A case study of a mattress protector company is presented to demonstrate a proof of concept.

This chapter is derived from:

**Sourabh Dani**, AK Rahman, Jiong Jin, and Ambarish Kulkarni, ‘Real-time Cloud Empowered VMS’, published for the special edition of ‘Handbook of Real-time Computing’, Springer.

## 4.1 Introduction

The advent of technological innovations in recent years coupled with the proliferation of CPS led to the rise of Industry 4.0. Industry 4.0 enabled the vertical integration of several key developments, such as hybrid machines, storage systems and production facilities, all of which are capable of autonomously exchanging information, triggering actions and controlling each other independently (Wang et al., 2016). These innovations have led to fundamental improvements in manufacturing, engineering, material usage and supply chains, as well as the life cycle management of industrial operations. In particular, recent developments in cutting-edge ICT technologies have led to the introduction of real-time applications for industrial manufacturing that entail more precise design and rigid frameworks for successful implementation, thus further automating processes. In the context of Industry 4.0, these advancements have made manufacturing processes more systematic, efficient and economically competitive, not only bringing about a new paradigm (i.e., hybrid manufacturing) but also establishing it as the hallmark of the fourth industrial revolution (Kusiak, 2018).

At present, the manufacturing sector and its associated businesses are highly competitive. Manufacturers are faced with the continual challenge of delivering pioneering methods for production at a reduced time to market. The emerging movement towards globalised advanced SM environments demand real-time information exchange between the numerous stages of the product development life cycle (e.g., product development design, operational setup, manufacturing planning, task scheduling, operations, packing). Along with this, flawless task collaboration between the different stages is also expected. Further, with increased environmental consciousness and regulation, more limitations are being placed on product disposal to support product recycling, repair and refurbishing activities. Unfortunately, such product development processes run the risk of becoming progressively more complex as products become more adaptable, intricate and intrinsically complicated and as product variants multiply in the trend towards customisation. To address such limitations, hybrid manufacturing technologies to support efficient and precise engineering decision-making capabilities in real time have been created through the establishment of versatile technologies, and the merging of existing manufacturing tools (Kang et al., 2016).

## 4.2 Existing Smart Manufacturing Framework

The application of VR and AR technologies is a promising recent innovation. These technologies help simulate and enhance SM procedures before they are conducted. Further, they ensure that the stages of production unfold accurately and efficiently in the first attempt without the need for redrafts and alterations (Nee, Ong, Chryssolouris, & Mourtzis, 2012). While automated manufacturing processes are an established method of practice, research on the manufacturing applications of VR and AR is relatively nascent. In fact, the dynamic interaction of current AR applications, enabled by the sharing of information with real working environments, has the potential to provide efficient and complementary tools to assist the hybrid manufacturing process. However, there is a need for a higher order of accuracy, response and interface design. A key challenge involves designing and implementing integrated VR and AR manufacturing systems that enhance the manufacturing method, as well as product and process development, to ensure shorter head times, reduced costs and improved quality (Nee & Ong, 2013). The eventual goal is to integrate VR and AR technologies with automated services in manufacturing provided by service robots. This integration within SM mimicked a real-world application (e.g.: DT). In addition, SM introduces the concept of the virtual factory (Choi, Kim, & Do Noh, 2015), which can generate information on the structure of states and the behaviour of systems, as can be observed in real manufacturing operations. Overall, SM presents an integrated computer-based model, which represents physical and logical schema of real manufacturing processes and exhibits real-world behaviour in its virtual performance. SM plays a significant role in reducing the cost of the product life cycle and helps test and validate the accuracy of a product and process design. However, SM has certain limitations. While SM offers the benefits of quality, a shorter cycle time, flexibility, responsiveness and customer relations, there is significant room for improvement in performance and efficiency.

This is where the IIoT offers so many opportunities. By taking advantage of the emergence of cloud infrastructure and wireless technology, IIoT offers the ability to integrate autonomously identifying evolving vibrant and complex industrial applications. Past industrial revolutions, such as mechanisation, mass production and digitisation, were followed by major changes during Industry 4.0. These advancements led to incipient autonomous technologies in the manufacturing industry that transformed traditional practices into smart technologies (Shrouf, Ordieres, & Miragliotta, 2014). Due to its unique characteristics of virtualisation, decentralisation and real-time capabilities, Industry 4.0 is anticipated to be a key area for the injection of IIoT, particularly in automating applications, such as detecting, instrumentation and observing for manufacturing applications through the insurgence of CC and wireless technologies. As stated by (J. Liu, Xu, Zhang, Zhou, & Pham, 2016), IIoT summarises the design code of industrial machine sensors unified with affordable computational costs and network resources. It has protracted its operational abilities and modifies wireless applications, from machines interacting with humans on repetitive tasks to solving complex multi-objective problems in uncertain environments and manufacturing autonomously. Although IIoT has facilitated the use of wireless sensor networks to further automate industrial processes, it also adds considerable complications in terms of decision-making and coordination. As previously mentioned, cloud infrastructure services can be leveraged to enhance the performance and efficiency of a system.

While SM (see Figure 15) is already a well-established entity, improvements in overall efficiency could be made by integrating CC, autonomous sensing, AR and VclusterR in newly developed and proposed virtual manufacturing operations in Industry 4.0. This could be further aided by the use of DT to pave the way for the smooth integration of the physical and cyber worlds in the context of manufacturing (Qi & Tao, 2018). While AR and VR help provide virtualisation for the preparation of product manufacturing (Hochhalter et al., 2014), DT can emulate real-time applications and run them in real-time while analysing the detailed changes that occur, which the physical equipment can subsequently react to (Rosen, Von Wichert, Lo, & Bettenhausen, 2015). Thus, overall, SM has the potential to integrate the above-mentioned entities and prepare rigid manufacturing processes that perform efficiently and accurately during the preparation, production and maintenance of operations. While generic proposals for such integrations are available in the literature, specific use cases should be studied to validate the scope of operations and analyse the performance and efficiency of systems. Therefore, a key research aim of the present work was to develop a framework to bring these technologies into a single platform using the specific use case of an automated mattress protector.

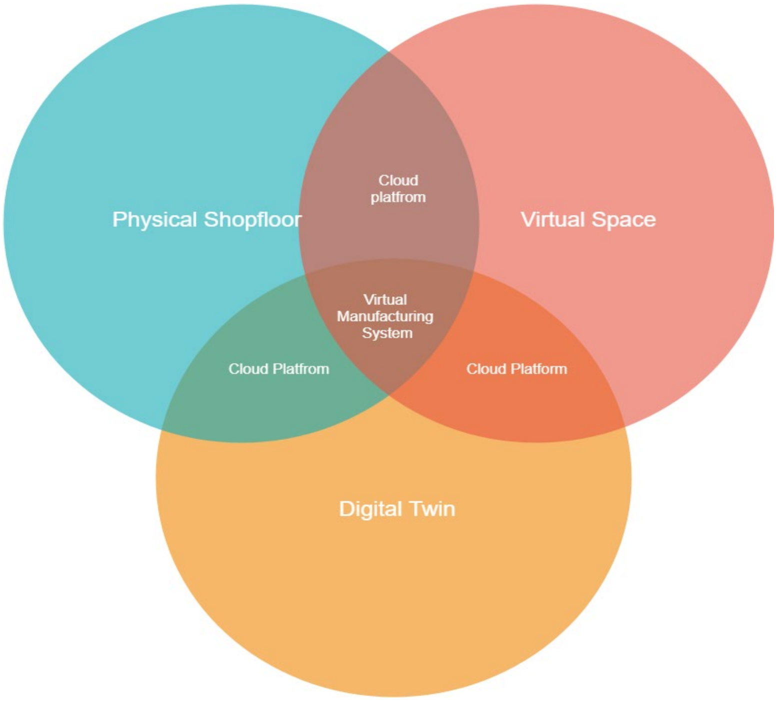


**Figure 15 Overview of smart manufacturing**

To achieve this objective, it was first necessary to understand the basic requirements of the technologies involved. IIoT technology must have various machines embedded with sensors that can communicate with each other, as well as the cloud to provide data and make decisions. Meanwhile, augmented and VR systems consist of sensor displays and use dedicated software. Altogether, this chapter concentrates on efficiently integrating IIoT and AR/VR onto a single platform to fine-tune the SM operation, where additional real-time analytical support is provided by DT. Given the challenges of combining these technologies, the novelty of this work lies in laying the framework for an SM process with multiple integrated entities and validating it with a proposed use case of an automated mattress protector whereby the proposed components are used in existing industrial operations. It is estimated that the proposed integration could yield an efficient virtual manufacturing system. The main contributions of this chapter are as follows:

i) A novel framework is proposed to integrate machine sensors and AR/VR on a common platform of cloud-empowered SM with real-time support from DT. The challenges associated with implementation, as well as development of hardware and software solutions related to the implementation of real-time, cloud-empowered SM in Industry 4.0, are presented.

ii) A use case of an automated mattress protector manufacturer is developed with specific details of the components of the integrated system outlined to complement the proposed framework. This is followed by a proposal of the operation details of a hybrid assembly line for a modelled SM to validate the approach in the context of a real-time industrial application.

The rest of the chapter is structured as follows: first a literature review that details the current state of the art and the challenges involved in integrating machine sensors with AR, VR and DT for a SM is presented. To overcome this, a framework for real-time cloud-empowered SM that explains the components individually and provides hardware and software details to integrate the entities is proposed. This is followed by the use case scenario of the application of automated mattress protector manufacturing. The components involved are listed, and an in-depth analysis of how they relate to the proposed framework is provided. To validate the system, the specification of the software and hardware components required is explained, and a hybrid assembly line operation is demonstrated to provide an overview of the SM operation. Lastly, concluding remarks are offered, and possible directions for future work are outlined.

## 4.3 Framework of Smart Manufacturing

An SM cluster (Figure 16) is a model of the implementation of a manufacturing process using a computer system. The use of a virtual environment allows for estimate predictions and an analysis of the possible problems associated with productivity and the ability to manufacture digitally before the actual manufacture takes place (Kimura, 1993) (GJ, 1995). SM is, therefore, a plan for a practical process whereby a simulation is conducted by applying virtualisation techniques using highly reliable computing devices and super-speed networks. Here, the aim is to realise the product planning, make design decisions, configure the manufacturing processes, and conduct performance investigations and quality reviews of the product manufacturing across all levels of manufacturing management. It also places control in the hands of decision-makers to enhance decision-making capabilities and regulate the capabilities of manufacturing industries (Choi et al., 2012; Kang et al., 2018; Kimura, 2017; Linthicum, 2016; W. Liu et al., 2016; Monostori et al., 1996; Quan-Deng & Yi-He, 2012; Sahl, Dupont, Messager, Honnorat, & La, 2018; Skarin, Eker, Kihl, & Årzén, 2019; Sqalli, Al-saeedi, Binbeshr,

& Siddiqui, 2012; A. Sun, Gao, Ji, & Tu, 2018; Sung, Han, & Kim, 2019; Wang et al., 2014; Yang-Turner et al., 2019; Q. Zhang, Zhu, Bian, & Peng, 2012; Y. Zhang, Zhang, Hao, & Yu, 2018). Although SM has gained considerable momentum in recent years, the concept itself is not new. The original idea of creating real-world models in virtual and augmented environments stems from the idea of artificial reality presented by Miron Krueger in the 1970s, and that was later suggested as VR by Jaron Lanier in 1989. Initially, virtual and augmented realities were presented as computer-generated 3D models with high rendering and animation to create an engrossing interactive simulated reality (Ellis, 1993). The term 'smart manufacturing' gained traction in early 1990 in the domain of aerospace, earth moving equipment and automobile industries. Over time, recognition of SM increased, as did the technology required to allow the concept to evolve. One such enabling technology was VR; this served as the basis for the manufacturing industry and aimed to address consumer demands and those of product manufacturers while maintaining cost efficiency and measured lead times. SM has the potential to rapidly develop data sets with technology infrastructure, as it facilitates the rapid expansion of manufacturing practices without adding significant cost to the operational time (Banerjee & Zetu, 2001). However, as with the success of any technology, many challenges remain, and there is need for further development.

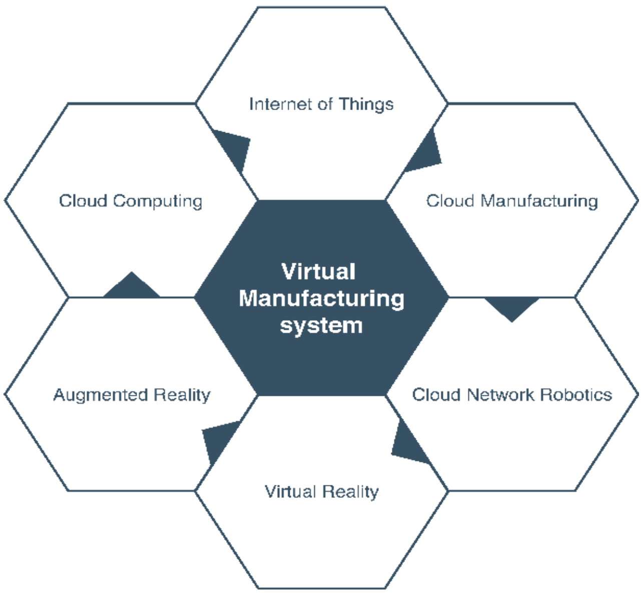


**Figure 16 Cluster presentation of smart manufacturing**

Specifically, pressure on manufacturing industries has increased due to increased customer demands towards products. At present, customised and diversified products are becoming ever-more popular. As manufacturing procedures and product designs become more complicated, the process of design–making in many specialties, such as product designing, manufacturing industries and production analysis, requires the consideration of many more parameters (Hitomi, 2017). Poor decisions can be detrimental to companies and cause significant losses. Therefore, there is a need for robust and well-defined methodologies for appropriate decision-making and process controls in industrial applications.

Unfortunately, making the best decisions requires significant experience, research and expert opinion. While helpful in the short term, none can give a definite picture of the future. To keep up with developments in manufacturing, shortened production and delivery cycles, as per customer needs, as well as the ability to rapidly adapt to market change, is necessary. In recent times, the approach to handling challenges has been to review concepts in advance before proceeding with the actuals, thus ensuring that the approach taken is not overly costly. However, the cost involved in changes to a design in the theoretical design stage is calculated according to designers' time to review and modify the change. Once the conceptual design is finalised, it is released to production. At this stage, any changes required in manufacturing were mere cheap and time consuming. The cost of changing a design increase as the project advances from conception stage to prototype and finally ending with the production, sales and marketing. Ideally, manufacturing, quality inspection and test feedback should be provided to designers as soon as possible to maintain the product family integrity and ensure the continuity of infrastructure, as well as improving project and manufacturing investments. This is where advanced simulations can offer substantial benefit.

In pursuing these capabilities, companies today frequently use simulation as a main technology which has assisted the manufacturers in reducing the cost of the prototypes and increase the profitability. As per the current state-of-the-art, the time consumed while manufacturing new products can be reduced by representing the manufacturing systems in digital form. This can be achieved by using modelling and process simulation, without the hassle of examining physical prototypes. Perhaps one of the most timely and interesting solutions in this area is SM (Iwata, Onosato, Teramoto, & Osaki, 1995) (Onosato & Iwata, 1993). SM proposes the creation of a synthetic and integrated environment that is enhanced by software tools and systems, such as simulation and VR, along with real-time analytical support provided by DT (H. Sun, Li, Fang, & Gu, 2017) and cloud infrastructure, thus offering turn-key results for the entire product development process from design to manufacturing. Here, the main objective is to provide a way for engineers to develop, evaluate and simulate complex systems entirely on servers and rapidly conduct experiments to predict and evaluate the results of alternate manufacturing decisions before spending time and money on constructing physical mock-ups. Many industries, such as the aeronautics and automobile industries, use SM to reduce the costs and time associated with product development.

Overall, SM is a well-established method for product manufacturing and maintenance in different Industry 4.0 applications (Shafiq, Sanin, Toro, & Szczerbicki, 2015). However, the scope of improvement still exists in terms of performance, stability and maintenance. Future approaches should aim to effectively integrate the beneficial features of IIoT (machine sensors) and AR/VR with DT to improve the system applications while meeting customer demands for timely delivery and greater customisation. Therefore, in the present work, a framework to address the challenges of traditional SM was proposed. The framework integrated IIoT with AR, VR and DT and validated it through a use case study of a real Industry 4.0 application of automated mattress protector manufacturing, where cloud-empowered SM was implemented in real time.

## 4.4 Prepositioning of Components

The preliminary components for the cloud-empowered SM presented in Figure 18 comprised various sub-units, such as physical shopfloor, a virtual shopfloor and DT. The PS consisted of a set of different entities that included primitive machinery, network machine sensors, raw materials and a stack of half-produced products with interventions from engineers. Here, the systematised order of production had to meet the delivery requirements and the target cost and quality of production. In contrast, the VS was a cluster of models designed and developed in multiple dimensions (i.e., geometrical dimensions, physical appearances, machine behaviours, characteristics of the machine and fundamental rules).

The connecting thread was the cloud infrastructure, which helped merge the PS and VS and provided a platform for receiving data from each entity in an optimised manner. The CI also received real-time data and analytical support from DT, leading to suggestions for PM and multilevel optimisation in the maintenance of the operation. The DT also allowed for fused data convergence from both the PS and VS, providing more comprehensive and consistent information. Therefore, in this proposed cloud-empowered SM, the CI acted as the lynchpin for an integrated service platform, where physical manufacturing data, virtual manufacturing models and real-time analytical support were brought into a single platform to yield an efficient manufacturing process with real-time implications.

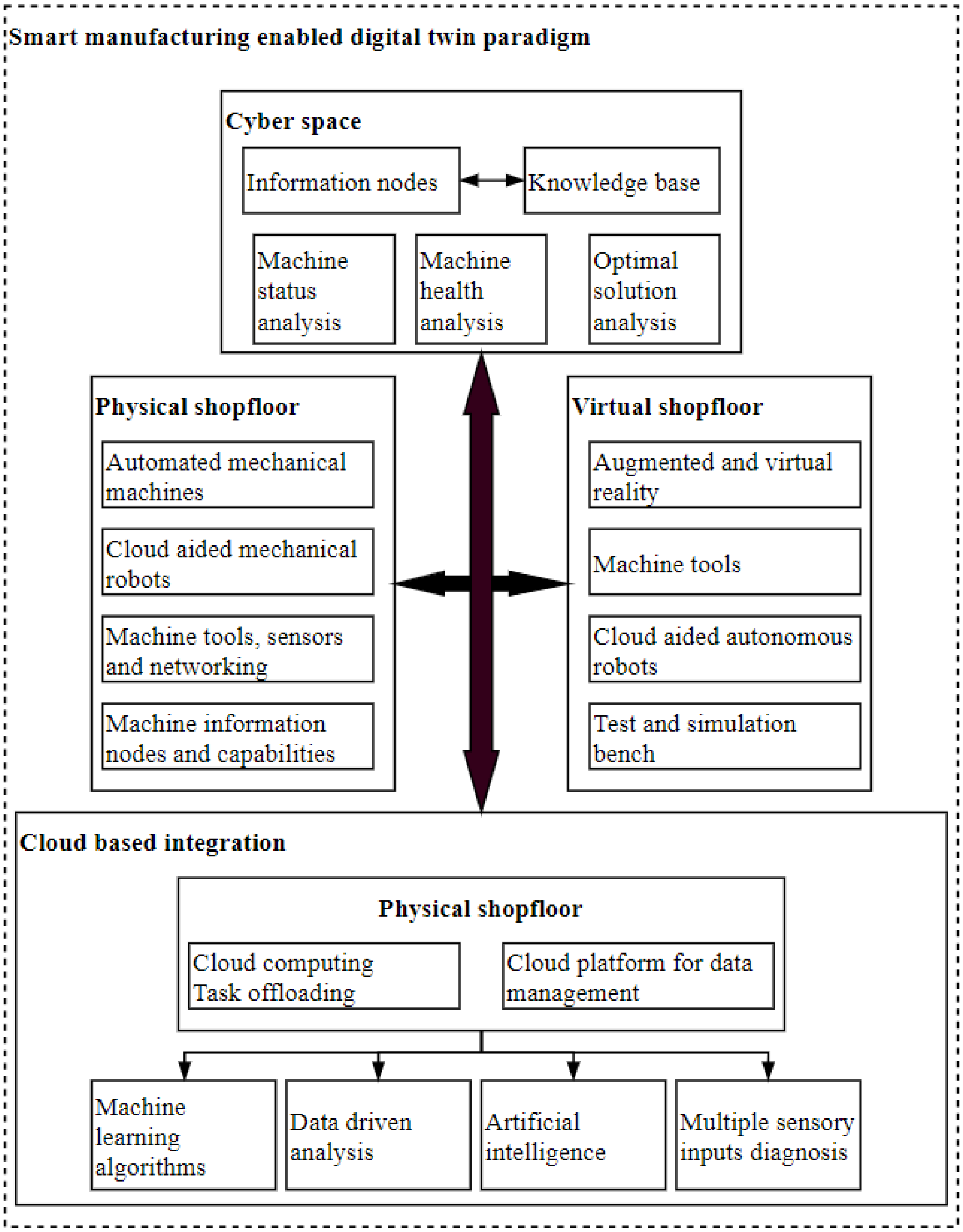


**Figure 17 Block diagram of real-time cloud-empowered smart manufacturing**

As shown in Figure 17, the CI acted as the driving force for the complete SM. For the PS, the CI updated the production order, stock in hand, stock to produce and raw materials required to manufacture the order quantity. In the VS, the 3D-designed models and their working mechanisms were built and updated according to the working status of the machine depending on constraints, relations between the different system operations and the rules of the physical shopfloor. Once the data had been fed to the VS, the CI sought to keep the workflow updated in agreement with future requirements to keep track of the machine health status and the working nature of future loads. Meanwhile, the CI updated the DT with the data received from the PS and VS to analyse the machine health and its working status and optimise the operation. Based on research from the DT, the CI then updated the workflow for the PS to achieve a better efficient working model in a real-world context.

Integrating the heterogeneous mediums of the PS, VS, DT and CI laid the foundation for a hybrid plant, which facilitated the hybrid manufacturing process. A structural presentation of the shopfloor is given in Figure 18. The hybrid manufacturing process improved the management of all the operations on the hybrid cloud-operated shopfloor. Here, the terms 'hybrid cloud-operated shopfloor' and 'cloud-empowered SM' mean the same and include operations on shopfloors, such as intelligent production systems and networked distributed facilities. The proposed integrated hybrid plant to not only harnessed the benefits of the hybrid cloud-operated shopfloor (cloud-empowered SM) components but also facilitated hybrid manufacturing. Hybrid manufacturing can overcome the limitations of traditional manufacturing methods and reach new heights in terms of efficiency and customer satisfaction. To meet the aforementioned goals of the proposed scenario, the system required a list of software and hardware that had to be integrated in the context of the cloud-empowered SM. The following section offers a detailed outline of the hybrid cloud-operated shopfloor and catalogues the required software and hardware requirements.

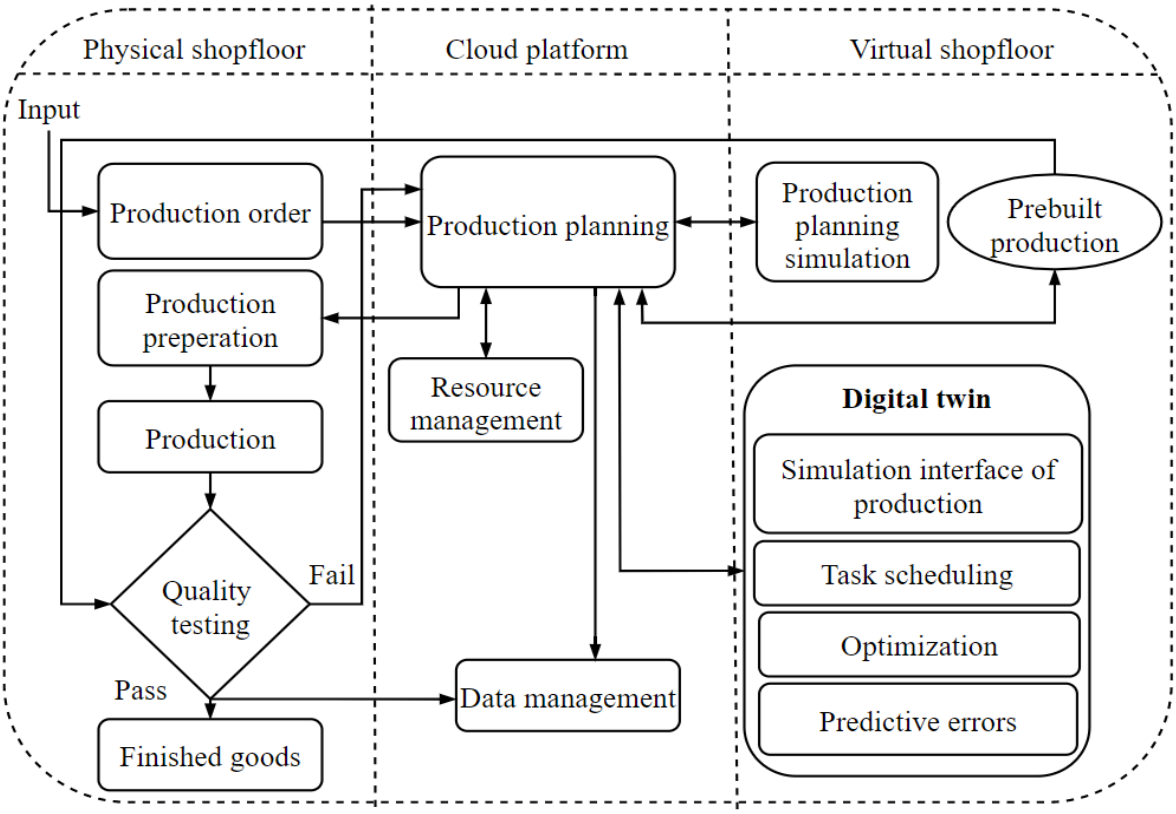


**Figure 18 Structural representation of shop floor**

## 4.4.1 Physical Shopfloor

The first and one of the important blocks of the framework is the physical shopfloor. This block consists of the all the physical machinery that integrate with the sensory inputs. Sensory information from the machineries is sent to multiple blocks for different purposes. The following sections provide details on the different machinery and their operations.

### 4.4.1.1 Automated Operations

The Eton system, as depicted in Figure 19, for home textile industries is fifth-generation hardware platform geared towards real-time operations for smoother production management and material handling. Chosen as the lynchpin for the physical shopfloor, the ETON 5000 consists of overhead conveyors with individually addressable product carriers capable of finding the path to the precise operation, thus eliminating the need for manual transportation and reducing handling costs ("Manufacturing of plastics, cabling and medicals," 2019). Monitoring support is provided by the interconnected computer network, which also supplies necessary data for accurate measurements and optimal process management. The system allows for modifications to be actioned rapidly during production line changes and expansion to be implemented when needed. The ETON 5000 is a flexible material handling system that radically increases speed and productivity, ensures an optimised workflow, allocates time to add value to the products and provides cost savings ("ETON To Display Extended Range ETON 5000 Production System At SPESA EXPO 2010," 2010), making it a suitable choice as for the PS.

**Figure 19 RFID Enabled automate operations (ETON 5000 syncro production system)**

Figure 19 present the ETON 5000 Syncro Production System, which transports the pieces of one unit of product (e.g., for mattresses, panels, borders and zippers) through different stages of production on a product carrier as part of the entire manufacturing process from pieces to production, resulting in a cost-efficient product (between 30% to 100% efficiency in terms of time, space utilisation and productivity). ETON 5000 was chosen as the production system (as a PS component) for the proposed cloud-empowered SM framework, where the unique system tool provided by ETON offered a wide range of options for hardware and software integration, as well as a smooth manufacturing through RFID application.

#### 4.4.1.2 Cloud Networked Operations

The Automatex CPT4700 (Figures 20 and 21) is a state-of-the-art automatic panel cutter in which one or two lanes of fabric is designed to be fed tensionless to the length and into a cross-cutting unit. The key features of the CPT 4700 that ensure a high-quality output are an electronic edge-guiding system, a servo motor-measuring system, an automated fabric in-feed tensioning system and a programmable length counter with touch interaction capabilities. It also offers remote control access and an evacuation conveyor that increases its market value.

Figure 21 presents the detailed components of the Automatex CPT 4700 Panel Cutter ("Home Automated Units,"). For the purpose of the proposed operation, the version with an output capacity of 8–12 cuts/min (which may depend on size), along with fabric width and cut length of 50–320 cm was chosen. Its power supply specifications were 208 V, 3 Phase, 50 Hz and 1.8 KW rating. With an air consumption of 6 bar/100 min and net weight of 2,600 kg, it was a superior choice compared with other manual operations as it showed greater accuracy and required less human interaction, making it a highly suitable choice.


**Figure 20 Cloud networked operating machinery (CPT4700 cutting machine panel cutter)**

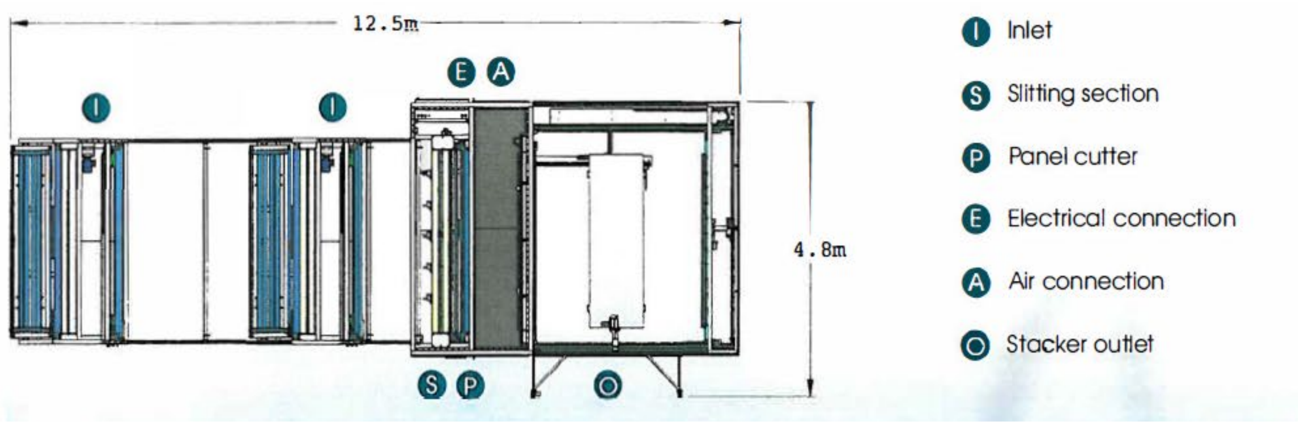


**Figure 21 Operational flow of the cutting machine**

### 4.4.1.3 Smart Practices

The Automatex Multitex 3300-2000 (Figures 22 and 23) is an automated folding machine designed to fold flat and book fold cardboard in flat products and fitted sheets ("Home Automated Units,"). The system has two sections: a loading section and a pre-fold section that may include three cross folds and two laterals with a double roll off stacker. Depending on the size of the operation, there may be one or two operators, which enable loading of the product on a vacuum conveyer with a view to holding the product in the appropriate positioning. It is used with a XV laser system.

In the pre-fold section, the cardboard is inserted with two lateral sections equipped with brushes to hold the material in place. The cross-fold section operates according to the swing-arm principle. The automatic press-unit is connected on the last cross-fold station to maintain the quality of stacking. This helps in the finishing stages when the folded and stacked products are transported to the exit conveyer once the process is completed.


**Figure 22 Smart folding solutions (Multitex 3300-200 folding machine)**

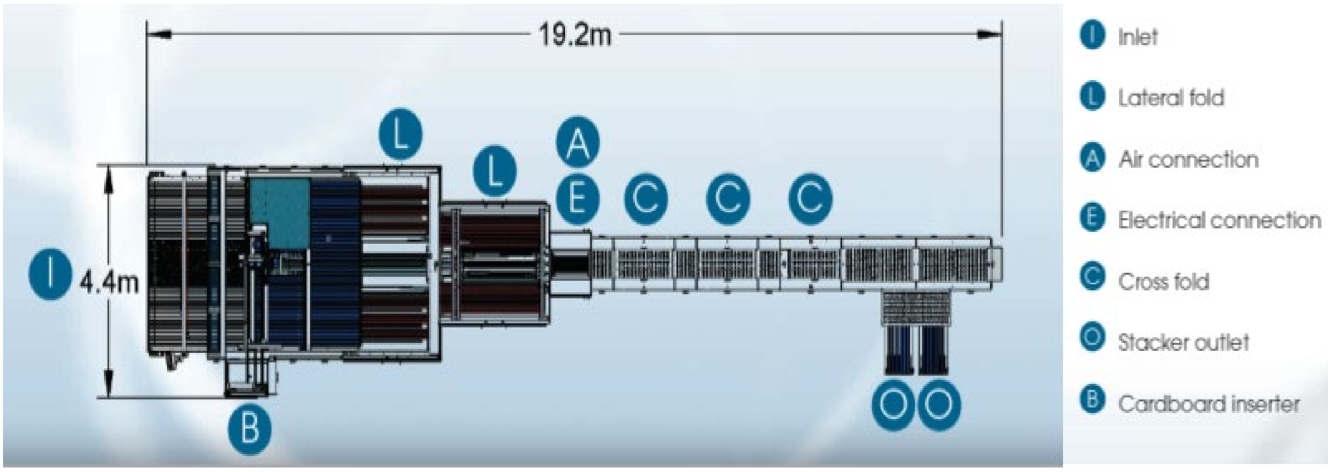


**Figure 23 Operational flow of the folding machine**

Figure 23 represents the operational flow of the folding machine. Similar to the panel cutter, the Automatex Multitex 3300–2000 also has key features that made it a strong choice (remote control access, interactive touch features, higher efficiency). Its other unique features include a motor-activated folding blade, which controls the operation, and a double roll-off stacker, which suggests a higher capacity. Importantly, the design of the cardboard allows easy access while providing automatic adjustments for flexibility in operations. The technical components for the operation of an Automatex Multitex 3300-2000 are presented in Figure 24. For the purpose of the given operation, the selected technical specifications were an output capacity of 12 units per min, a product size of 800 x 1000 mm to 3200 x 3200 mm, a folded size of 200 x 230 mm to 400 x 400 mm and power supply of 208 V – 3 phase – 50/60 Hz – 3.1 kW. The net weight of the component is 9,300 kg.

#### 4.4.1.4 Available Industry 4.0 Packaging Solutions

The next step of the operation included integrating Industry 4.0 packaging solutions. Due to variation in package dimensions and a considerably large amount of stock keeping units (SKUs), several different solutions could provide on-demand packing, as shown in Figures 24 and 25.


**Figure 24 X7 Packing machine from packsize**


**Figure 25 CMC carton wrap 1000**

On-demand printing is also crucial for successful integration. Packsize (Partnered w/VISY) ("X7 Packing Machine,"), ABBE PYT LTD and CMC CartonWrap ("CMC CartonWrap: The Unique 3D Box on Demand Machine,") are currently the leading providers of on-demand packaging solutions in Australia, offering similar features and functions. They use corrugated cardboard for packing purposes, which complements the global mission of bio-degradable packaging throughout the product range.

Additional customisation for automatic carton packaging systems can create dynamic cardboard boxes from simple and inexpensive (yet continuous) fanfold corrugated material in real time. This is managed automatically through real-time product recognition or direct extraction from a database, hence guaranteeing high flexibility during processing. Nevertheless, it creates potential challenge in branding the products after packaging with vital information and graphics, which is difficult to achieve in real time per product. To overcome this, some solutions for on-demand printing have been proposed, though they are either too expensive or difficult to integrate out of the box. The Trojan® T3-OP (Figure 26) and Limitronic V6 Titan (Figure 27) are two such systems that enable high-quality colour printing for different sizes and resolutions. In addition, ALTech ALline E - Front & Back Labelling (Figure 28) helps satisfy specific labelling requirements when applying tamper-proof seals to product caps. The labeller can save any parameter for specific label–product combinations and regulate the different units for format and product changes in a simple manner with high precision. These features made this combination of printers the ideal choice for the operation, in which a custom print and label on-demand solution was devised efficiently.

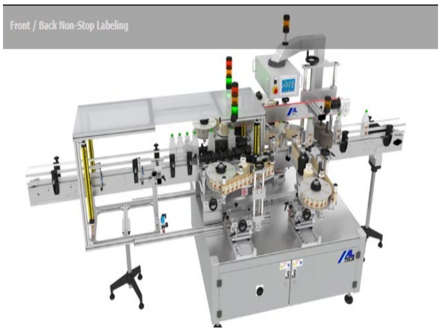


Figure 26 Front and back labeller


Figure 27 Smart systems

Figure 28 OnDemand printer

## 4.4.2 Virtual Shopfloor

The next important element of the SM framework is the virtual shopfloor. In this block, all the machinery from the PS was virtually modelled and designed for twinning purposes. The technologies used for twinning are detailed in the below sections, and CC deployment methods and types are discussed.

### 4.4.2.1 Cloud Computing

Cloud infrastructure is, as it sounds, a virtual space. Within this virtual space, the user is provided with a virtual machine that consists of all the elements required to make a workable machine, though all within the virtual space. This reduces the use of local servers, which, in turn, helps with the hardware and maintenance required to maintain the physical machines. To achieve all that CC is capable of, there are three main cloud-based applications, as follows:

i) Amazon Web Services (AWS). The success of AWS is proportionate to its dominance in the cloud market. Amazon has been a shareholder in the cloud market for over 10 years. The reason for the popularity of ("AWS,") is the scope of its operations. AWS has a complex network of worldwide data centres to maintain its operations. Although it is one of the biggest competitors in the cloud market, its biggest weakness is its cost. While running a high workload on the service, AWS finds it difficult to make the costs required for maintaining such an impressive level of service.

ii) ("Microsoft Azure,") Although late arrival to the cloud market, Microsoft Azure was able to gain market share by repurposing software it already had on premises for the cloud. It also attracted several leading companies, which bolstered its reputation and confirmed its reliability.

iii) ("Google Cloud Platform,"). The Google Cloud Platform specialises in slightly different things compared with Azure and AWS, offering big data, analytics and CC. Today it offers the ability to load balance for larger-scale operations. All the different Google data centres generally provide a fast response time. Although it has several advanced features, Microsoft Azure and AWS have a variety of software and features that make them more appealing than the Google Cloud Platform. The platform is, therefore, generally used as a secondary provider due to the appeal of AWS and Azure.

#### 4.4.2.2 Cloud-Deployment Methods

Cloud deployment has become complex with the growth of products. Today, applications must handle traffic outbursts and attain real-scale architecture. The emerging demand for new features and the regular deployment of fixes increases the complexity of the deployment process, particularly because moving servers is difficult. Some of the challenges of deploying a cloud application using outdated strategies are as follows:

i) Difficulty in scaling out is a manual process. It is impossible to scale out unless there is a deployment plan that helps add new servers on demand. This is a common challenge, as dependence on manual processes lowers the performance efficiency and does not allow extra servers to be added.

ii) Manual replacement during server outages in cloud-based applications should be robust and should replace servers using automated deployment. Manual deployment when replacing or recovering failed servers is time consuming.

iii) Application release during the maintenance window/timeframe is scheduled downtime for application releases. It is required if the deployment takes more time than expected. Immediate actions, such as bug fixing and deploying new features, should be avoided if the release occurs during the maintenance window.

iv) Runtime faults through deployment prevent few requests from working differently. Servers must have the same version of the code base; if not, few requests may give out different outcomes than others, which in turn makes it difficult to troubleshoot errors that occur and that are hard to debug. Runtime errors are common during long application deployment processes or rolling deployment involving several servers.

v) Unstable deployments succeed in some environments, while unpredictable errors arise in other environments, such as production environments, thus resulting in unstable deployment.

vi) Deployment breakdown is not a major problem, but if errors are detected after deployment and cannot be rolled or changed back, then it is necessary to run the error version of the application until the error is fixed. During deployment breakdown, the application is down or unavailable until an error-free version is deployed.

vii) Rare production deployments to the production environment should be frequent; otherwise, the probability of errors after application deployments increases significantly.

CC has been the greatest invention of Industry 4.0, particularly for integrating various technologies, such as IoT, DT and ML. However, CC is limited by latency issues when used in the context of the IoT. The manufacturing systems require large data set transfers between machinery to sensors through the cloud, resulting in computing inefficiencies.

The real-time computing powers of the SM framework for machinery require low latency in communication and high reliability in computational tactics. One solution proposed for the latency issue was the use of fog computing. Fog computing covered a discrete area of manufacturing to reduce the latency in communication from sensors to the cloud (Li et al., 2018). However, introducing another technology added complexity to system that resulted in unpredicted errors from system management. Another solution proposed involved connecting sensory data to the cloud by surpassing data transmitters or propagators. Connecting the data to the edge of the cloud decreased the latency, which enhanced the reliability of the SM (Lin & Lu, 2011; Linthicum, 2017). Once sensory data are collected, they must be processed. Validating data in real time is complex and time consuming. Fog or cloud edge solutions have been proposed for this type of data processing. Resource allocation is subsequently conducted through the management system to process the required data. A frequent concern has been the lack of resource optimisation, which results in data ambiguity with unforeseen errors. The procedure of pilot testing cloud-centric VS has been proposed as a means to overcome this issue (Maenhaut et al., 2017). Resource management in the cloud results in unforeseen errors with a high data demand in a limited amount of time. To resolve these errors in CC, specific novel algorithms have been fine-tuned or rewritten based on previous data sets (Rauscher & Acharya, 2014).

SM has the unique characteristic of demanding service-oriented networked manufacturing. This approach optimised and included several complex operations and yields dynamic operations of the shopfloor. Several frameworks consisting of integrated CPS, along with major technological alliances, such as a communication protocol between online (cloud) to offline services (physical machine), have been proposed. The SM has been discussed in various forms, however, lacks implementation instruction with practical approach (W. Liu et al., 2011). Along with SM, major technological verticals, such as the 3D printing of cyber models, have gained significant interest in recent years in terms of industrial advances, design, manufacturing and research. Researchers have explored how SM can be supported to boost economic growth, concentrating on inhouse manufacturing (Jawad et al., 2019). Innovations in manufacturing along the industry four standards have gained prominent importance in recent years with the integration of cloud manufacturing and IoT, which can overcome the conventional structure of the modern shopfloor. Researchers in Korea suggested an assessment tool for use in SM that was equipped with current manufacturing practices to understand the behavioural characteristics and future prospects of organisations. Adoptability of SM was prime important, specifically for individualised low volumes. These types of assessment tools can assist medium-sized enterprises and small-scale engines in emphasising Industry 4.0 approaches (Sheen & Yang, 2018).

Interconnection between implementation strategies, addressing issues and identifying smart solutions are the main goal of SM. However, previous industrial practices did not address configuration and customisation. To resolve these issues, an IIOT hub was proposed by researchers; this hub offered customisation and a programmed connection between the heterogenous operations and services, which were encapsulated and differentiated from individual behaviours (Tao et al., 2018). Addressing these heterogenous properties has expanded competition between major characteristically differentiated manufacturing industries. Due to global competition between industries, competitors have shifted their attention to automating their industries and implementing advanced manufacturing technologies across the production line. The main goal of implementing these technologies has been internal growth, operation optimisation and manufacturing efficiency (Lee et al., 2018).

SMEs have been in great need of advanced manufacturing practices. Cloud manufacturing has helped companies enhance their productivity, emphasising high-production volumes, better communications bracket cloud-enabled communications and computational services. Cloud manufacturing has the greatest potential to enhance the competitiveness of complex manufacturing industries. In a complex industry like textile manufacturing, product portfolios are enormous. To align with the development, design, implementation, management and computation must register the concepts and operations onto the cloud to be structured systematically (Bai et al., 2019). A challenging task involves managing services like pluggable inputs and outputs and plug and play services. These services have helped realise smart factories enabled by the cloud. Researchers have proposed many frameworks in cloud-based intelligent services, such as edge computing, CC and REST-based web services. One such framework used dual RESTful-based services to enable a PAM, where the production management of by manufacturing processes was handled remotely on an intelligent platform supported from PAMs to target individual services. This type of framework has been tested for the fast and reliable deployment of SM using cloud services.

PAMs can also facilitate PM (Fan & Chang, 2018; Liu, Hung, et al., 2018). Deploying these technologies on a cloud platform often presents difficulty in choosing between different cloud-deployment strategies. To define the clear path and choose the appropriate type of cloud, this chapter discusses the various cloud models. There are many ways to integrate the cloud to design the models and enhance current practices. Deployment can be defined according to the location of the infrastructure to be built, the control authority of the infrastructure and the designed model category. An important aspect of deployment involves selecting between the four major varieties of cloud models.

#### 4.4.2.2.1 Public Cloud

In recent years, the public cloud has become an influential model and is generally created on-demand for third-party users. Servers created on a public basis are only for on-demand public application over the internet for third-party users. Resources stored in cloud servers are on pay per usage basis whereby the user pays the provider. Some resources are standards supplied for a set amount, and others are on an on-demand basis, where costing is set based on quotes. Major market sharers for cloud sources are AWS, Microsoft Azure and the Google Cloud Platform. These cloud providers have extended their branches extensively across the industry and have helps automate complex manufacturing industries. Studies across cloud deployment have suggested that security and latency issues are key challenges when storing data on public cloud domains (Hahn, Kwon, & Hur, 2018; Kaneko, Ito, Ito, & Kawazoe, 2017; Kim, Wang, & Humphrey, 2015; Ko, Tan, & Ng, 2014; C. Li & Yang, 2018; Liao & Su, 2011; Malatpure, Qadri, & Haskin, 2017; Mangal, Kasliwal, Deshpande, Kurhekar, & Chafle, 2015; Min, Park, Lee, Cho, & Kim, 2011).

#### 4.4.2.2.2 Private Cloud

This type of cloud model deployment offers a private space or network for computational services. The private cloud is highly versatile, and accessible service points are locally managed by regional data centres. Research has shown that access points that are assigned were designed to adapt to the private cloud for their existing system (Naik, Beaty, Vogl, & Sanchez, 2013; Park, Yun, Kim, & Yeom, 2017a, 2017b; Qing, Boyu, Jinhua, & Qinqian, 2018; Ramamoorthy & Poorvadevi, 2018; Rauscher & Acharya, 2014; Sahl et al., 2018). Private cloud deployment is more secure compared with public cloud. The major drawback of these systems is the high cost of the investment, as the core of the system design was conducted by local administration.

#### 4.4.2.2.3 Community Cloud

This type of deployment is similar to private cloud deployment but with one major difference: task optimisation in a single cloud with tasks of a similar nature happens in the background rather than on the consumer end. Several organisations share cloud resources and infrastructure to address a similar set of issues and benefits. If the sharing organisations has uniform security, performance and privacy optimisation, then the community cloud is addressed with the help of data-centric architecture (Bellini, Cenni, & Nesi, 2015; Carson, Thomason, Wolski, Krintz, & Mock, 2019; X. Chen, Wang, Wang, & Jin, 2018; Gordon, 2016; Khan & Freitag, 2017). This extension is often used in managing multiple manufacturing operations and sharing limited and optimised resources.

#### 4.4.2.2.4 Hybrid Cloud

Hybrid deployment is a mixture of public and private cloud services. This type of cloud deployment handles tasks and computational services on a priority basis. As such, real-time computational services are handled by on-premises private cloud providers, while the latency carried services are often managed by public cloud (Gordon, 2016; Grefen, Vanderfeesten, & Boultadakis, 2016; Linthicum, 2016; Loghin, Ramapantulu, & Teo, 2019). Scalable information must be stored and used according to task priority. Deployment must be more redundant and proactive compared with other types of deployment due to the dual nature of computational promises.

Challenges have occurred due to limitations in implementation, services, computational ability, efficiency in terms of data handling and virtual machine management. Several considerations must be made when implementing in a real-time environment. The following section details the available service models required to complete the functionality of the model.

### 4.4.2.3 Cloud-Deployment Strategies

#### 4.4.2.3.1 Downtime Reduction

There are proven strategies for reducing actual downtime, such as removing servers and re-adding removed servers (e.g.: serialised deployment) and background applications. This common strategy works for nearly all possible deployable programming scripts, frameworks and server environments. Another important aspect of deployment strategy is that they can be deployed in parallel with all the servers of the domain to deploy at a single instance, which is often called 'parallelised deployment'. By considering the whole infrastructure as independent instances, the deployment strategy can be altered to independent deployment steps in parallel. Further, the entire stacks of infrastructure can be swapped, including all the necessary infrastructure components, to start a fresh stack to the latest version of executable instances. It is important to note that not all applicable approaches may work or be the best fit for the team process. Automation support is key to finalising the appropriate downtime.

#### 4.4.2.3.2 Rollback on Failure

The automated process works without error in most instances. However, there can be occasional deployment failures that occur for several reasons, such as software bugs, issues in the deployment steps or infrastructure failure. The ability to roll back in any instance is key to restoring a suitable stable version of an application. Failing to account for this during deployment leads to prolonged downtime. The rollback process of an application should include a variety of steps, including:

i) reverting to the previous stable version as soon as possible and restarting the process associated with the application
ii) Updating DNS entries to the previous version on which the infrastructure was working and reworking on the available services
iii) reverting the recent database with migration steps.

If the above steps are not followed, it is difficult to recall all instances of the application to instate the working order. This means that the application suffers from rollback delays.

#### 4.4.2.3.3 Scripting

Human error can occur at any step in the deployment process that is not scripted. As the deployment process is established, scripts that perform repetitive tasks are built. This prevents skipped steps or errors in typing that can sabotage deployment. Deployment scripting can be handled using server configuration automation tools or build automation tools, such as Jenkins, Codeship, Bamboo and GoCD.

#### 4.4.2.3.4 Version Control

The code should be versioned and tagged on release to ensure a complete snapshot of the application is available at any time. In addition, version and tag deployment scripts alongside application releases. This provides insight on changes over time and allows for application rollback using the proper deployment scripts. Script versioning also captures changes in the history of the deployment process over time.

#### 4.4.2.3.5 Continuous Integration and Deployment

As an application grows, it is important to know when changes to the code may break the application. Here, automated test coverage can help ensure that an application is functioning as expected and that fixed bugs do not regress. By automating the build and integration testing of an application (when code changes are committed to a central branch), teams can be immediately alerted if a change breaks a test. This technique is known as ‘continuous integration’ (CI). CI builds on the practice of using automated tests, automated deployment scripts and version control for application deployment and has become commonplace for many software products companies. Continuous delivery is the practice of automating the entire process of building and deploying a release to a specific environment that may require additional review or acceptance before final deployment. The goal is to deploy early and minimise the number of changes between releases, thus avoiding the ‘big bang’ deployment problems of major releases.

Continuous deployment varies from continuous delivery in that the goal is to fully automate the flow, from code changes to production deployment, through a series of automated processes within each application environment. While the feature may be deployed in production, its exposure to internal teams, select customers or all customers can be limited through the use of feature toggling.

#### 4.4.2.3.6 Repeatable Deployment Across Environments

Applications commonly have more than one environment. In development/integration, developers deploy most recent features for integration and developer testing QA/UAT, and internal testing and customer acceptance testing (where applicable) are conducted to verify the quality and expected behaviour. Staging/pre-production mirrors a production environment. Production data are used to identify issues or data migration failures. Production is the customer environment with production data. As the latest changes to the application moves forward to each environment, different teams qualify changes to ensure a stable release into production. If the cloud infrastructure, resources and settings vary greatly, bugs that are difficult to troubleshoot and that can be missed completely until production release may be introduced. To avoid this, versioned scripts are applied to the infrastructure automation scripts and deployment scripts. Table 1 outlines the methods and related deployment strategies detailed in the earlier section of this chapter.

**Table 15 Cloud strategies and relative measures of deployment**

| Strategy | Downtime Reduction | Real-time traffic testing | User objective Scripts | Cloud expenditure | Rollback interval | Adverse effect user | Setup complexity |
|---|---|---|---|---|---|---|---|
| Recreate | × | × | × | ★☆☆ | ★★★ | ★★★ | ☆☆☆ |
| Ramped | ✓ | × | × | ★☆☆ | ★★★ | ★☆☆ | ★☆☆ |
| Blue/ green | ✓ | × | × | ★★★ | ☆☆☆ | ★★☆ | ★★☆ |
| Canary | ✓ | ✓ | × | ★☆☆ | ★☆☆ | ★☆☆ | ★★☆ |
| A/B testing | ✓ | ✓ | ✓ | ★☆☆ | ★☆☆ | ★☆☆ | ★★★ |
| Shadow | ✓ | ✓ | × | ★★★ | ☆☆☆ | ☆☆☆ | ★★★ |

## 4.5 Smart Manufacturing Framework

The components of the SM framework are discussed in detail in the following section. This section covers the components used when designing the framework that was studied for the best feasible and fit models.

## 4.5.1 Framework Components

The proposed assembly line of the hybrid SM integrated AR, VR and cloud services with physical machinery as part of the same virtual manufacturing system. The application was set up in the context of an automated mattress protector manufacture based on the components presented in section 4.1. The process included the cooperation of various heterogeneous modules, and the overall integrated system is shown in Figure 29.

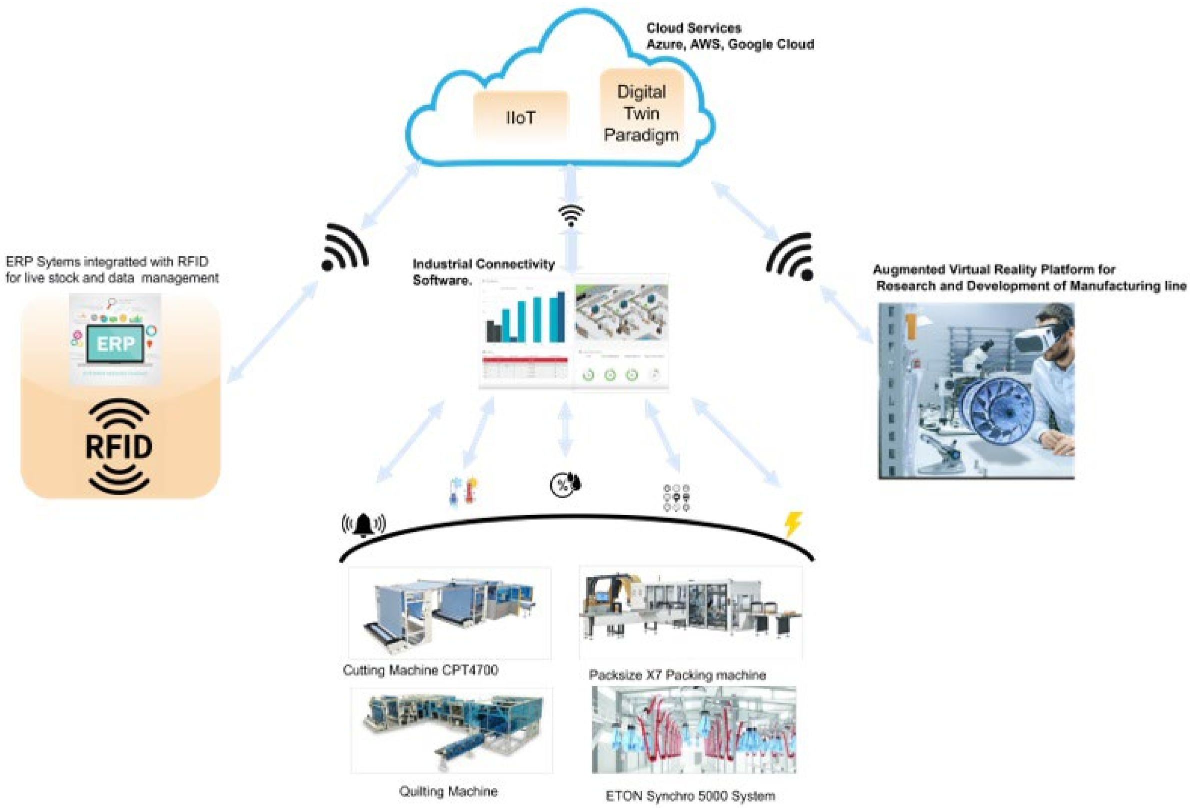


**Figure 29 Modular presentation of smart manufacturing**

### 4.5.2 Details of Components

As shown in Figure 30, the modular presentation of the SM consisted of the following sections:

i) The PS consisted of hardware machinery for cutting (CPT4700), production and material handling (ETON Synchro 5000 System), as well as a packing machine (Packsize X7). These machines provided an automated service and were monitored by local engineers for further maintenance and monitoring. The machines also had sensors embedded that fed real-time data to the system. They were integrated with the RFID along with the ERP system for real-time stock management, order management and emergency order or order dispatch management. These components provided data to the cloud via the Internet.

ii) Another key component was the AR/VR platform, which aimed to identify approaches to researching and developing the manufacturing line.

iii) Analytical support regarding management/computation/decision-making related to stock management, machine operations and approach modification via DT was provided through cloud infrastructure that had the required capability.

iv) Industrial connectivity software was the lynchpin of the system. This software was the central communication platform that accepted inputs from physical shopfloor, RFID integrated ERP systems and AR/VR development platform. From this point, all the information was transferred to the cloud through two-way communication.

In the context of the automated mattress protector operation, the manufacturing unit included a number of units that worked collaboratively with other verticals in a rhythmic pattern, interacting with each other to yield a mattress protector in a precise and efficient manner. The automated mattress protector manufacturing system used a specific panel cutting machine (CPT4700), the real-time customisable packing machine Pack size-XP, the sewing machine Rimac 396H and the ETON Synchro 5000 system (as shown in Figure 29), which constituted the physical equipment. The efficiency of work during mattress protector manufacturing was calculated, along with the computational cost of the existing practice of manufacturing. Further, the number of resources required, such as human resources, power resources, safety measures and lead time to conduct the operations was estimated to determine the proficiency of every machine to help ascertain whether improvements were needed. It helps engineers on the shopfloor work precisely while also inspiring more industries to follow the same path.

Complimentary to the physical shopfloor, the proposed hybrid model used a virtual machine to monitor the work characteristics of the machinery with the help of IIoT, DT, DA, AR/VR and ML technologies. Each of these technologies served a unique purpose. For example, the ML analysed the data collected from the machines to run learning algorithms, produce predictions and estimate a machine's characteristics. The algorithms that were programmed to attain stable and consistent growth and promote work efficiency were stored in a cloud platform (as the cloud can hold large amounts of data, content or information). VR created a virtual scope of the physical apparatus, replicating it to near-reality so that the user need not be physically available or use equipment to determine the work characteristics of a machine. Lastly, the DT was a platform that allowed the work conducted by a machine to be monitored in a virtual environment that was internally connected to the physical environment. This virtual replica of the physical machine was in running mode or twin mode. These technologies were intertwined during the manufacture of mattress protectors, where machines performed proficiently without the need for much human labour, freeing workers from laborious tasks.

On the right of Figure 29, a VR represents the virtual apparatus of the machines. In the context of this operation, it refers to the virtual apparatus of the CPT4700 cutting machine (i.e., the CPT4700 is visualised as a machine sitting in any part of the world using VR equipment, such as Oculus Rift, Google daydream or other VR equipment). By wearing VR headset, it allows the viewer to see a virtual machine in front of them that imitates the real machine while not being physically present in the manufacturing factory, thus helping to ascertain the performance of the cutting machine. The characteristics of the physical machine (e.g., the time period, dimensions, temperature variance, speed and load) can be assessed. The virtual cutting machine has the same characteristics of the machine, though it is virtual. All the above three modules are connected to a cloud platform (e.g., Azure, AWS or Google cloud server), where learning algorithms (e.g., ML) play a key role and are fed with inputs of the CPT4700 characteristics to predict or estimate the work efficiency, performance rate and other parameters of the virtual and physical machine, which is integrated as a part of the DT technology. In this way, the proposed work not only improves on the current setup for the manufacture of mattress protectors but also widens the scope of study in this field to enhance the smart factories of the future.

### 4.5.3 Operational Process

The assembly line operation of a single unit automated mattress protector is shown in Figure 29 and was based on the aforementioned components and proposed framework. The CPT4700 cutting machine was the physical machinery, and its work characteristics were predicted. The goal was to estimate the work characteristics of this machine virtually. Industrial connectivity software collected data from the CPT4700, such as electricity and heat usage and speed, and stored it for multiple scenarios from the sensors. Various data, such as electricity consumption by the machine when manufacturing a king-size mattress protector, the amount of heat produced when the machine ran continuously for eight hours, the amount heat produced when the machine was operational for one hour and the speed of work, were monitored. Data on how efficiently the CPT4700 worked for various targets were also collected and pre-processed for computation (including the battery efficiency of the machine while the machine was operational and the battery output when the machine was at rest). As shown on the left side of Figure 29, an ERP system integrated with RFID stored information on the machinery in the factory, such as livestock, data management, orders placed, machines delivered and machinery in-repair state. Each machine was allocated a unique RFID.

### 4.5.4 Operation Flow

This section elaborates on the production flow of the use case (i.e., the operational flow of mattress protector manufacturing flow), as depicted in Figure 29. The operation begins once the production order is generated and is passed on to verify production planning and resource management. The flow is then divided into two verticals with a view to simplifying the process planning and resource allocation. This allocation helps in production planning, accumulate the required production planning, data acquisition, data simulation, task offloading and future prediction analysis. Resource management is further divided into the two verticals of process and inventory management to help use the available resources for manufacturing purposes.

### 4.5.5 Manufacturing Planning

In the production planning stage, once an order for a mattress protector comes into the factory, the order must be planned. Planning can only be conducted if the user knows the previous history of a similar order. If not, the planning team must plan according to resource availability. A user cannot create a new plan for every order; therefore, they must use advanced technology to pace up his credibility and increase efficiency. The proposed framework for the operation is geared towards this approach, as the pre-production planning block of the flow is initiated. In this block, historical data are analysed to plan the intended production. Once an order enters the pre-production simulation, it matches with similar available historical data to give the user an estimated time of arrival for the order.

After preproduction, the simulated data are stored for future reference. In this context, the data management is conducted in a sequential manner to accomplish the futuristic simulation. Once the data acquisition is complete, the next task for the planner is to assign the task (offloading). The planner must manage the set of commands to achieve the best possible solution for the resources available. They match the resources with the available resources in the virtual environment, which provides the estimated time of production. While simulating the estimated time for production, several precautionary measures must be taken (e.g., machine breakdown, machine maintenance, unexpected power down).

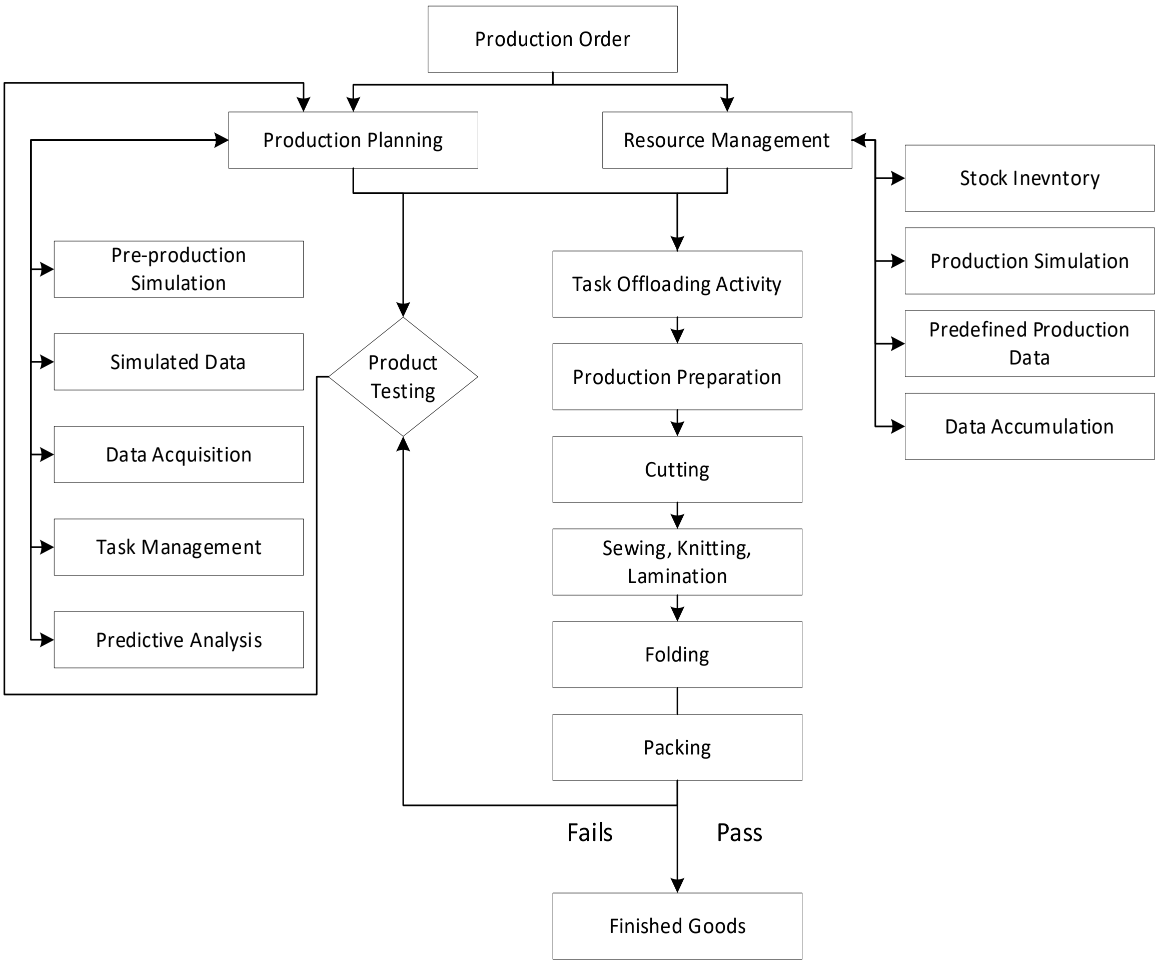


**Figure 30 Operational flow of production in smart manufacturing**

To overcome unexpected errors in the physical world, a range of issues is simulated in the virtual world. Tasks should be handled appropriately by the important block of the virtual or digital world, which is called predictive analysis. Predictive analysis provides an in-depth analysis of unexpected errors and scheduled maintenance based on the history of a mattress protector manufacturing plant, which assists the planning process.

## 4.5.6 Resource Management

Next in the production line is resource management. This is divided into two major verticals: process flow and inventory management. Inventory management is required to manage, and supply required materials for the production of a particular order of a mattress protector. Once an order is simulated in the virtual world, and the test results of the virtual world are satisfactory to the planner, it is passed onto the inventory manager to supply the required materials needed to process the order.

Once the stock inventory is complete, the next action involves managing and matching the process data with the simulated data to enable the data for the production order to be generated per requirements. This data differs from the data simulated in the virtual world for reasons such as materials defects, machine defects, machine operating environment restrictions and other practical issues. Hence, these data must be properly managed and logged to overcome future delays in the production progress. Once all tests are completed, the data are accumulated in the next block for use as future reference.

The next block in the production flow is the manufacturing process. After receiving the required materials and mattress protector orders from the planning team, tasks are offloaded in the practical or physical world. Tasks are offloaded according to the job priorities and the process flow. Following this, production preparation decisions must be made. For example, a cutting machine must be assigned to a panel that is cut in a particular way for a given set of an order. The Eton lines or conveyor line should also know where to cut the panel sheet to be assigned for sewing purposes. The sewing machine must then be selected based on the kind of interlocking stitch being performed. The folding machine is subsequently notified of the type of folds required to be performed for that order. Similarly, the packing machine must be informed of the kind of packing required, the printing machine must understand the label required, and the inserting machine must be clear on the type of inserts to be made for the order. These are key aspects of decision-making in relation to resource management in the proposed SM. While these sets of operations are theoretically simple, synchronising the individual operations during actual execution is far more complex. The practical solution is to bring everything onto a single platform and integrate the mattress protector with RFID technology. The machines listed above are capable of RFID communication in real time. The task of transferring the product (i.e., a mattress protector) from one stage of production to the next must be synchronised. This synchronisation requires a better understanding of the operations, including the production time, downtime, material handling time and operator handling time. In this regard, the tasks must be managed with the assistance of virtual simulation in synchronisation with the practical data to ensure the flow of the automated manufacturing operations.

## 4.6 Chapter Summary

This chapter described the design of a conceptual SM framework for a manufacturing company. The SM framework addressed challenges within the manufacturing industry. The framework harnessed an integrated cloud-based SM framework interlinking MES and ERP. This provided efficiency gains, enhanced communication and facilitated flexible manufacturing for personalised low-volume manufacturing.

i) This chapter proposed a framework for the operation of a real-time, cloud-empowered SM system. Numerous innovations in the field of SM were reviewed to identify the key components required with a view to integrating them in the proposed SM framework. In this way, the proposed concept merged the VS and PS with a DT via a cloud platform to maintain seamless data integration and communication. This ensured smooth decision-making and the process flow from pre-production, through production, all the way to packaging and beyond.

ii) Contrary to similar work, the proposal was further validated via a detailed use case study for an automated mattress protector manufacturer. Detailed specifications of the components required were presented, followed by the actual operational flow. Therefore, the comprehensive operations of a fully functional virtual manufacturing system were presented based on the proposed novel framework. This proposed approach made the mattress production much productive, time efficient and economical. Aside from practical executions, future attempts in this domain should focus on integrating DT in real time with physical and virtual shopfloors (as opposed to current approaches that revolve around theoretical data). Further, integrating CNR would also fully automate the SM while also making it more efficient, which will be a focus of future studies.

iii) The main challenges that occurred when developing the framework were the control of machine characters, which resulted in inefficiencies related to increased costs; high latency issues of the cloud; demands for product personalisation due to global market competition; and ineffective communication between workers and machines, which resulted in waste.

iv) SM could represent a solution to the challenges of inefficiency, low-volume manufacturing and decision-making frameworks. The LR indicated that SM is a key solution that has been the subject of research, though it lacks practical implementation strategies. Further, research has only explored implementation in singular approaches that address one problem at a time. The LR revealed a lack of research on integrated multiple transformative technology usage, such as SM, in a holistic way.

v) Transformative technologies (e.g., ML, CC, CNR and AR/VR) were used to capture the manufacturing operations characteristics. AR/VR technologies were used to visualise the operational flow and for the time analysis and simulations. These inputs helped attain vital data for analysing the behaviour of the machines by incorporating ML algorithms for PA in future. These tools, integrated into a cloud platform, showed potential for addressing key manufacturing challenges. Once the integration of the technologies was migrated to the cloud, the operation was handled by high-end computational programs. These computational programs were designed according to the virtual commissioning output from AR/VR layout. Based on these results, a conceptual framework was proposed for implementation.

vi) SM-integrated approaches in previous works lacked decision-making analytics and, consequently, lacked better communication protocols. The communication process lacked an effective transfer of technological precedence between various roles. Collaboration between different roles and machines using advanced tools was found to lack the integration required in prior practices. New trends in wireless communication have given a broad understanding to the real-time integration of the digital and physical world. Seamless data transfer and the integration of tools have made manufacturing more efficient and effective compared with traditional practices. Along with communication, advanced technologies used for prioritised computing and offloading the tasks were missing in traditional practices. While these technologies have been explored in theoretical terms, there was a gap in terms of their practical implementation.

# 5 Efficient Smart Manufacturing

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This chapter illustrates the implementation strategy of the SM framework in a manufacturing scenario. The chapter first discusses the data generation and collection strategies before outlining the results and analysis.

This chapter is based on:

**Sourabh Dani**, AK Rahman, Paul Shuva, Jiong Jin and Ambarish Kulkarni, 'Cloud Empowered High Dimensional Anomaly Detection', submitted to the internarial journal of IEEE.

## 5.1 Introduction

Integrated information systems play an important role in manufacturing. To address the traditional ongoing challenges in manufacturing, an anywhere, anytime strategy must be applied and verified. This chapter focuses on ways to overcome efficiency issues in manufacturing. The chapter covers the following aspects of SM:

i) Section 5.2 introduces the integrated SM system. This system introduction is powered by cloud operations, which is dedicated method of data management.
ii) In section 5.3, the life process of the manufacturing data is discussed in detail. This section explains the data collection from sources, data storage and management, data pre-processing and data realisation. Raspberry Pi module was used to collect data, and the challenges associated with this are discussed in this section. The data storage and management section detail the cloud management and explores how to retrieve the data from sources. Further, the pre-processing methods of the manufacturing data are discussed along with the methods used for realisation.
iii) In section 5.4, a data-centric system empowered by cloud instances is discussed. This section seeks to explain the high-dimensionality of the data generated by the manufacturing machinery. The methods of dimensionality reduction, its advantages, methods, possible and best fit algorithms are discussed.
iv) In section 5.5, high-dimensional data analysis using two main algorithms is discussed. These algorithms have been widely discussed for their scalability, usability and versatility in relation to the implementation strategies.
v) Lastly, section 5.6 discusses the self-leaning algorithms. The results obtained from implementing the ML algorithms on the manufacturing data are presented.

## 5.2 Cloud-Empowered Data-Centric System

The IoT and the data accumulated from sensors in manufacturing systems is a continuous process. Data production is a never-ending process, and methods are required to analyse and define these data and to understand the behaviours of machines (Caesarendra, Wijaya, Pappachan, & Tjahjowidodo, 2019). If data are left unanalysed, need for integrating these machines with the required sensors and communication protocols is redundant (Lei et al., 2018). The number of machines that are sufficiently smart enough to generate data continues to grow. This rapid growth cannot be ignored. An estimated 3 exabytes of data are generated every day, which is equal to all the data produced by IBM systems in previous years ( Lin et al., 2017). This amount of data cannot be stored on personal computers or locally generated data base storage systems, which would be hard to access. For this reason, major companies, such as Microsoft, IBM, Google and AWS, have provided on-demand cloud solutions (Grefen et al., 2016; Nguyen et al., 2017; Zhang et al., 2012).

These data can be further be treated as an information source, and, in return, the same data can be used for future predictions. However, this transformation of data from information to knowledge cannot be handled by sensors or local analytical platforms (Leng et al., 2020). This is where cloud empowerment for data analytics steps in. Figure 31 depicts the general architecture of a cloud-empowered data-centric system in which the manufacturing system data is transferred to the cloud system. This data transfer occurs through multiple fast and reliable communication protocols, such as WLAN, Bluetooth, WSN and Wi-Fi.

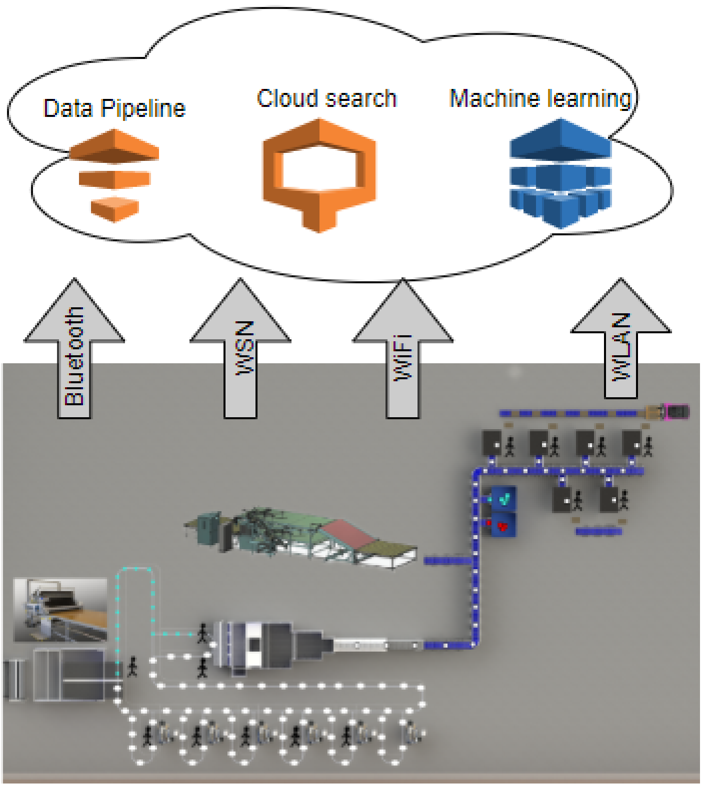



**Figure 31 Cloud empowerment in smart manufacturing**

This integrated system has evolved by incorporating reliable sources of sensing technology (Jawad et al., 2019). Sensors for every possible expectation can be incorporated into a machine. In the architecture presented in Figure 31, data from sensors are collected and stored in the cloud environment for processing. Aspects of the data, such as scalability, elasticity, economic benefits, reliability, security on storage and accessibility for predictions, are justified using cloud empowerment. The efficient and effective computing of data stored in the cloud is important for extracting useful and important features. Data generated from heterogenous machines are of very high volume, wide variety and intense velocity. The concept of big-data concepts can help understand the 'three Vs' of data (Ding et al., 2019; Lin et al., 2017; Yao et al., 2017). Many providers around the world have taken the initiative in managing databases. The foremost among them are Apache Hadoop, Oracle, Cassandra and Vertica. These providers perform the jobs of storage and computing, which allows consumers to make use of the data in a virtual scenario.

## 5.3 Life Cycle of Smart Manufacturing Data

Manufacturing systems use many important machines that provide information that is vital for analysing the life cycle of the production. It is important that every machine on the shopfloor meets the required efficiency. Efficiency can only be achieved by balancing the production line. The performance matrix of the production line can be improved by installing advanced technologies. These technologies are data driven and prediction accuracy increased with the more data. The following sections detail the collection, management, and processing of data.

### 5.3.1 Data Collection from Sources

The data sets manager from various technologies provide visualisation in manufacturing to enhance decision capabilities (Leang, Ean, Kim, Chi, & Yoo, 2019). MES handles data streams between manufacturing machines, while the ERP platform assists in planning the inventory of the organisation and the product life cycle management. Modelling software, such as computer-integrated manufacturing and computer-aided design, also assists in manufacturing in the virtual world. Four main types of data can be collected using this system: machine data, management data, inventory data and general data. These data are explained below:

i) Machine data are data collected from sensors built into the equipment. These data include data on the machine behaviour, real-time execution, maintenance scheduling and history of the equipment. These data are crucial in deciding which of the collected data are useful so that they can be processed and analysed for the concrete understanding of the operation.

ii) Management data are data generated by the manufacturing management system. Such data are often generated by the team that has planned the execution of production, such as MES and ERP. These data often provide information on production planning, scheduling, inventory management, sales, distribution, warehousing and forecasts.

iii) Inventory data are typically collected from sensors that are integrated into the product itself, such as RFID, barcodes and QR code systems. Inventory-tracking data are useful when manufacturing teams are integrating their systems with their customers or providers. These data help the system to store, track and manage data related to the manufacturing date, batch of production and warranty.

iv) General data are usually generated from research and development teams and include data related to the development of technology and integration of advanced protocols. In particular, this type of data allows manufacturers to guarantee the implementation of advanced technologies within their practices.

In this era of big data, with the help of IT, manufacturers can easily obtain and process data to enhance production. Access to manufacturing data has allowed a range of manufacturers, including the SMEs, to implement technologies and enhance productivity.

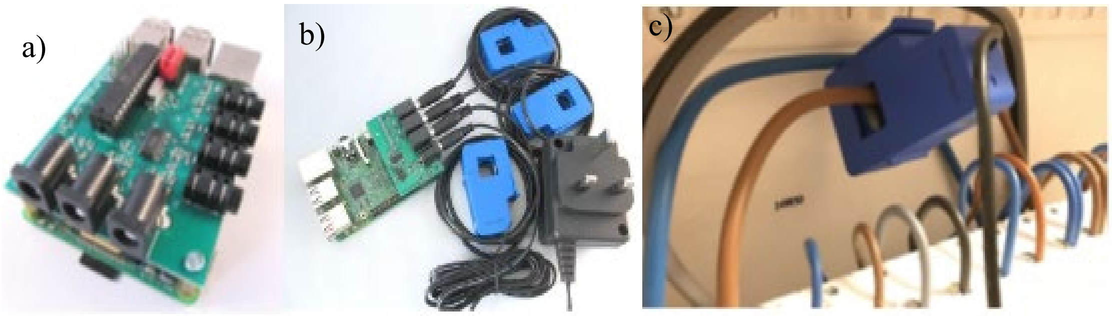



**Figure 32 Data acquisition from physical machines a) Raspberry Pi module, b) power reading clamp and c) integrated module**

### 5.3.2 Data Storage and Management

According to IBM, the data generated from manufacturing systems daily exceeds 2.5 exabytes. Storing and managing these is a challenge for any system. However, fortunately, certain cloud systems can make life easier for manufacturers by allowing them access the data they need with ease (Jaensch et al., 2018). These data can be often classified into three categories:

i) Structured data sets are often readily usable for any type of analysis with algorithms or basic modelling, such as digits, tables and symbols. One drawback of this data type is that it is not highly descriptive. Often, some analysis and research are required for this data type.

ii) Semi-structured data are partially understood by the direct user; however, this data type is not self-descriptive. This category of data includes data trees, XML documents or graphs generated by a system. These data require a knowledgeable practitioner to handle and manage.

iii) Unstructured data sets are easy to understand visually, but realisation is challenging. They include data sets, such as images, videos, audio files and system logs. Data realisation falls under the special section of data engineering, image recognition or pattern recognition to understand the machine behaviour.

Initially, manufacturers tended to rely on structured data sets, as they were easy to manage. Now, object storage stores data in a designated object and stores the key invention of a storage system, which is far more convenient and easier to analyse compared with file systems or block storage. This is because file storage stores data on a single file, irrespective of the data type, while block storage stores data in singular blocks of data and further stores these data sets as separate pieces of data. The advantage of object storage over block and file storage is that data are easily accessible for analysis, retrieval and optimising resources while also being cost competitive.

### 5.3.3 Data Pre-processing

Data collected from manufacturing systems often require cleaning. Cleaning refers to a series of steps involved in processing data in need of refining, as depicted in Figure 33.

The collected data must be processed and converted to yield useful information that can be used to make critical manufacturing decisions (Jia et al., 2019). Processing filters null values and misleading, inconsistent and redundant values within the collected data set. Data processing also removes duplicates and finds missing inputs, which constitute impurities within data sets. Data pre-processing is conducted in six stages, depending on type of data:

i) Batch processing processes data collected in batches from machines. These data are often used in the later stages of analysis. This type of processing does not help in manufacturing; rather, it is useful for payroll systems.

ii) Real-time processing collects and analyses data in real time. One drawback of this processing is that it can only be conducted on small amounts of data, such as in ATM machines. Although this is prime need in manufacturing, real time synchronous analysis is limited due to large volume of data.

iii) Online processing does not process for null values or duplicates; rather, the data are fed directly onto the servers, where they work directly on the analytical algorithms. Often, this can only be done on one system at a time.

iv) Multi-inputs processing, multi-inputs or parallel processing is a type of data processing that is often used when there is more than one data point, and multiple servers are required to process the data. This type of processing is used when researching the weather or in the online streaming of live events.

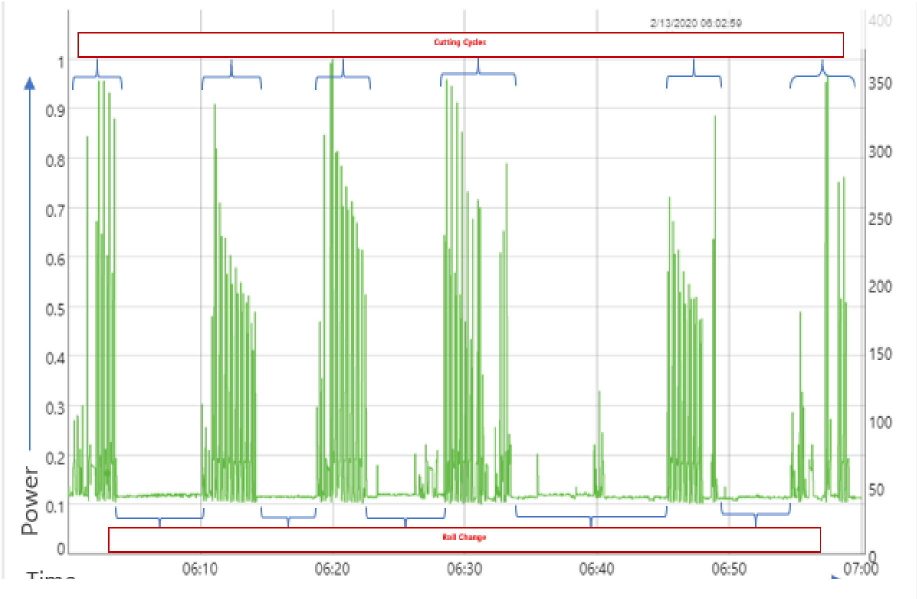



Figure 33 Power data analysis

### 5.3.4 Data Realisation

Once the data are collected and pre-processed, they must be visually realised (i.e., a presentation method must be implemented on the data set collected). Such realisation can only be performed with the help of ML algorithms, data analytical formulas, graphs, tables and figures. Realisation helps manufacturers understand their stand when compared with similar data sets generated from virtual or CPS systems. The analytical results can subsequently be further compared, and effective implementation measures taken. Figure 34 shows a pivot table generated from the data collected from a typical machine on the shopfloor for a number of sheets manufactured in given amount of time.

**Figure 34 Pivot results from collected data**

| Process | Definitions | Data | Results | Planning | | |
|---|---|---|---|---|---|---|
| **Object Type** | | | | | | |
| **Model** | Object Name | Data Source | Category | Data Item | Statistics | Average Total |
| **Model** | Model | NumInWIP | UserSpecified | StateValue | Average | 7.3177 |
| **ModeEntity** | | | | | Final Value | 11.0000 |
| | | | | | Maximum | 16.0000 |
| **ModeEntity** | Queen | [Population] | Content | NumberInSystem | Average | 1.5127 |
| | | | | | Maximum | 7.0000 |
| | | | FlowTime | TimeInSystem | Average (seconds) | 94.9607 |
| | | | | | Maximum (seconds | 148.9808 |
| | | | | | Minimum (seconds) | 76.1057 |
| | | | | | Observations | 400.0000 |
| | | | Throughput | NumerCreated | Total | 403.0000 |
| | | | | NumberDestroyed | Total | 400.0000 |
| | Single | [Population] | Content | NumberInSystem | Average | 4.6296 |
| | | | | | Maximum | 13.0000 |
| | | | FlowTime | TimeInSystem | Average (seconds) | 89.2010 |
| | | | | | Maximum (seconds | 155.9064 |
| | | | | | Minimum (seconds) | 69.3057 |
| | | | | | Observations | 1305.0000 |
| | | | Throughput | NumerCreated | Total | 1312.0000 |
| | | | | NumberDestroyed | Total | 1,305.00 |
| | Superking | [Population] | Content | NumberInSystem | Average | 1.1754 |
| | | | | | Maximum | 6.0000 |
| | | | FlowTime | TimeInSystem | Average (seconds) | 101.2347 |
| | | | | | Maximum (seconds | 152.0274 |
| | | | | | Minimum (seconds) | 84.7057 |
| | | | | | Observations | 292.0000 |
| | | | Throughput | NumerCreated | Total | 293.0000 |
| | | | | NumberDestroyed | Total | 292.0000 |

## 5.4 Data-Centric, Cloud-Empowered Smart Manufacturing

Data from the manufacturing shopfloor were collected, processed and analysed using ML technology. Implementing ML technology within manufacturing enhances the intelligence of decision-making frameworks. Data-centric modules focus on the important modules of the application. Examples of such modules include:

i) shopfloor modules, which are used for a variety of industrial tasks. Shopfloor modules are made up of a number of different IT services and industrial resources that may be used in man-machine-material environments. Inputs for these modules are the raw materials of the manufacturing industry, while completed goods are end products. Enormous amounts of versatile heterogenous data are acquired from machines, manual labour, machine operators, production systems and industrial networks during manufacturing.

ii) Data principled modules. Data principled modules cover many phases of the industrial data lifespan and serve as the driving engine for SM. Data from production modules are sent to cloud-based data centres for additional analysis as inputs. The operations of the manufacturing module and relevant decisions are automated using data analytics (e.g.: actionable suggestions derived from various types of raw data). The data-driver module also provides power to real-time monitoring and problem-solving modules.

iii) real-time interfacing module. These modules are facilitating real-time supervising of the production process to assure product quality. They are driven by the data-driver module and can analyse the real-time status of production facilities. This allows producers to keep up with changes in the manufacturing process and build the best operational management methods possible. When a machine is idle, for example, raw material is dispersed, and a material path is tracked. Specific product quality problems can be addressed by altering the production process. As a result, the real-time interfacing module can improve the efficiency of industrial facilities.

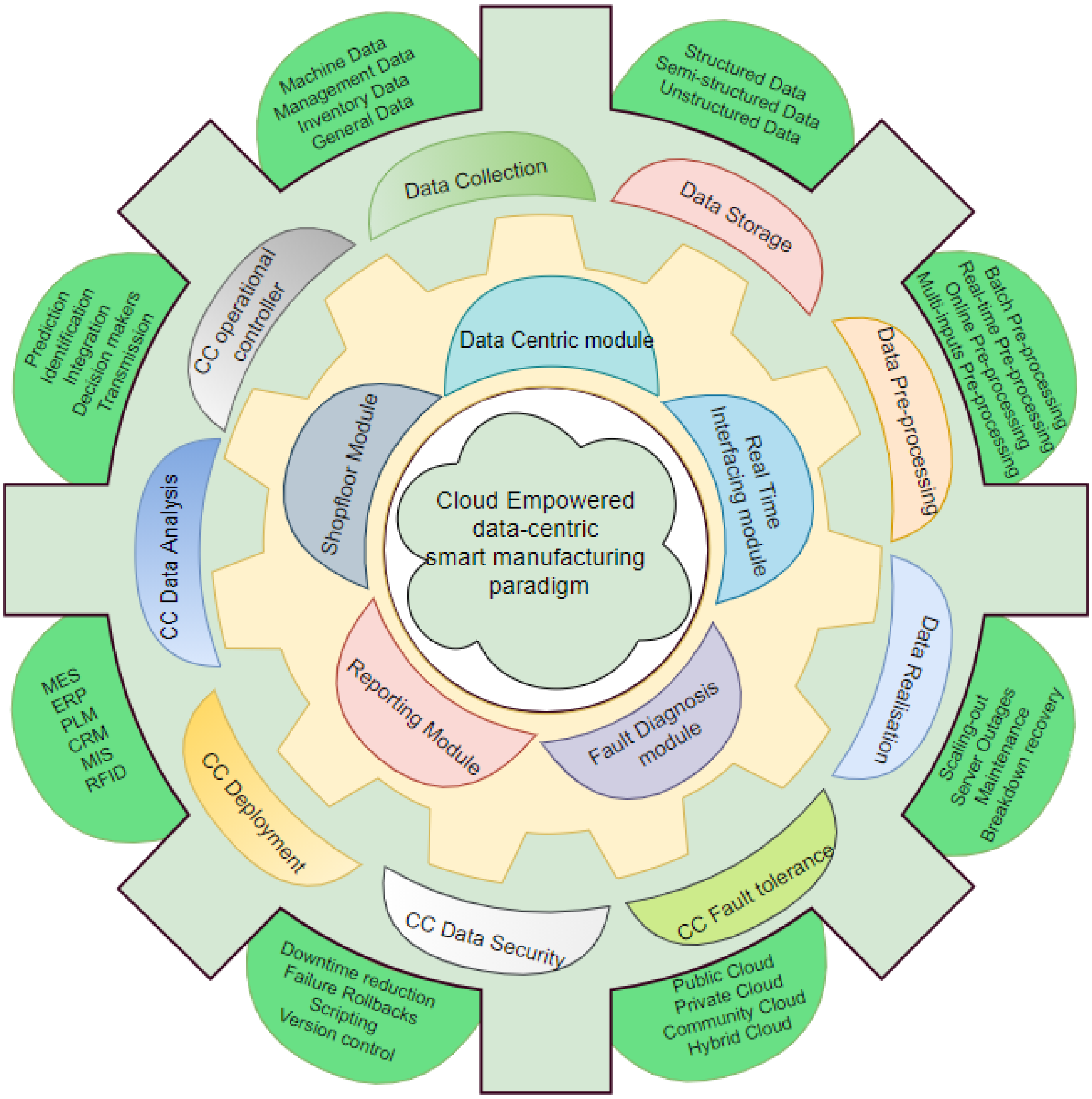



**Figure 35 Cloud-empowered data-centric smart manufacturing paradigm**

iv) fault diagnosis processing module. These modules can detect and predict future problems (e.g., equipment failure or quality flaws), diagnose the root causes, recommend feasible remedies, estimate solution efficacy and assess potential consequences on other manufacturing operations. Programmers or AI practitioners can make educated choices based on real-time data and the assessment of past and current data. This is facilitated by the data-driver module and allows existing issues to be handles while also preventing similar problems from occurring in the future. This module's initiative-taking maintenance improves the smooth operation of industrial operations. Data compilation, incorporation, storage, assessment, visualisation and application are organised processes that can be applied in a variety of businesses. Here, data-driven SM architecture is generally useful. SMEs and large corporations can choose different ways of accomplishing data-driven SM at different scales based on resource availability. SMEs, for example, can use on-demand CC services supplied by third parties, such as Amazon and Alibaba, while larger firms can afford to create exclusive cloud infrastructure for data storage and analysis. The core value propositions of data-driven manufacturing are the same for SMEs and large corporations, regardless of where and how the data are handled. Manufacturing data help decision-makers quickly understand changes, make correct judgements and develop rapid-reaction methods to solve problems. As a result, production schedules, manufacturing operations and resources can be carefully linked to maximise efficiency.

v) The researching module. This is an important aspect of the specified framework because it researches all aforementioned modules. The researching module is programmed with multiple pieces of software and hardware and concentrates on all possible faults, issues and recoveries. Faults are often important and researching module diagnosis and provides appropriate reasoning. Decision-making strategies that hinge on the results generated by these systems play a vital role, as changes often have lasting effects.

The difficulty of detecting patterns in data that do not conform to expected behaviour is known as 'AD' (Martí, Sanchez-Pi, Molina, & Garcia, 2015). The AD problem, by definition, depends on the data or application in question. To provide a comprehensive overview and comparison of a variety of approaches to AD presented in the scientific literature, including examples from industrial damage detection and medical AD. Think about the irregularity location issue using a multi-variate time arrangement dataset collected from sensors installed on fabricating gear on a production line. The issue of inconsistency discovery is particularly challenging, as inconsistency information records are constrained, anomaly designs are sporadic, and discovery must be precise in a timing design. To date, some approaches have been proposed, as discussed in chapter 3. Traditionally, rule-based arrangements are connected for discovery. The rules are specific to the encounters, space knowledge advertisement hoc information examination.

Subsequently, it is defenceless to the unseen anomaly and cannot be effectively generalised to other fields or situations. CC procedures have risen in prominence as volumes of data have increased (Karim, Ranjan, & Shah, 2020; Stojanovic, Dinic, & Stojanovic, 2017). Some approaches are based on time arrangement analysis models, such as autoregressive coordinates moving.

### 5.4.1 High-Dimensional Data Analysis

This section presents a case study that illustrates how implementing technologies alongside physical machines can overcome traditional challenges. This case study centres on an Australian mattress protector manufacturer, as illustrated in Figure 36. Mattress protectors are a key component of human wellbeing. They offer protection from bed bugs and other pests that live on bedding. Further, they protect mattresses from stains, such as coffee spills and oil spills. As shown in Figure 36, the input is raw fabric passing through various operations in textile manufacturing (e.g.: slitting machine to cutting machine). The manufacturing involves a series of intrinsic production processes: slitting, cutting, sewing, folding, packing and warehousing.

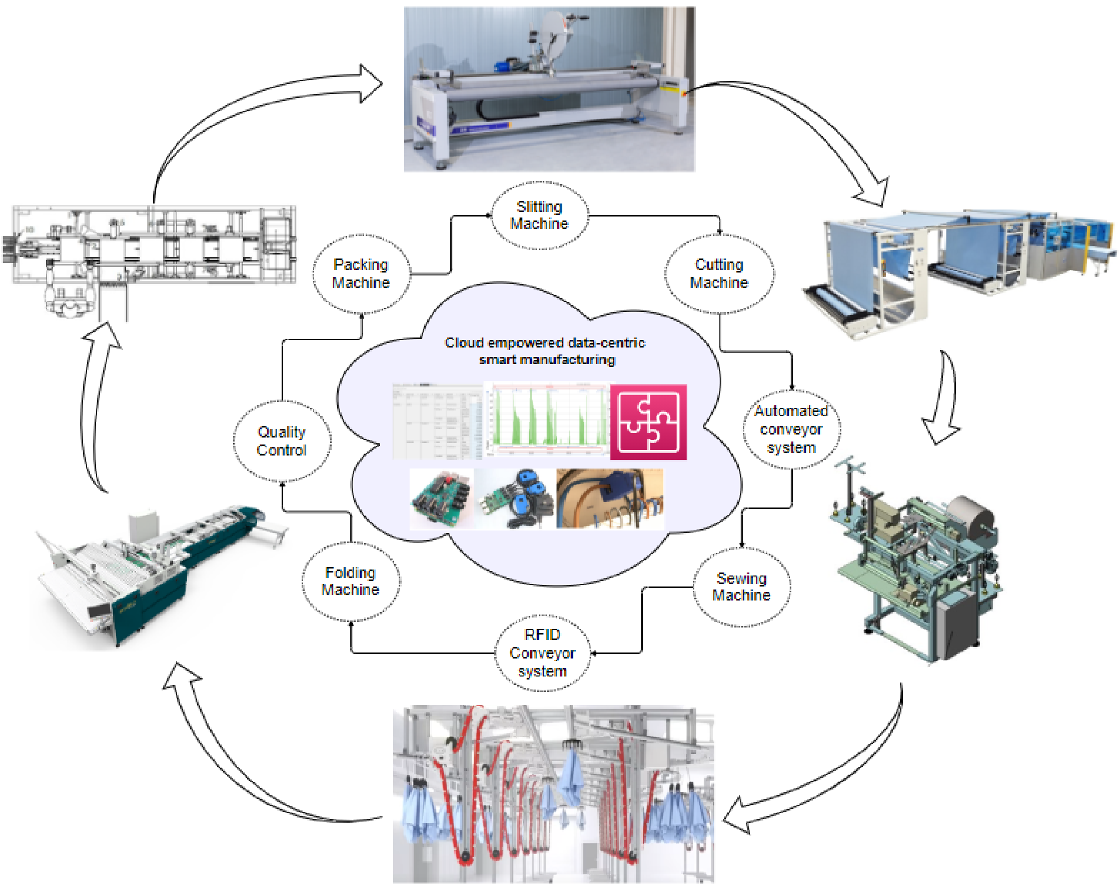



**Figure 36 Data-centric smart mattress protector manufacturing**

As the industry is craft oriented, operations are often intrinsic or heterogenous in nature. Further, the operations require human intervention at every stage to ensure the production process, quality control and compassion in manufacturing. The speed of operations can be improved by introducing advanced machinery capable of self-diagnosing faults, transferring data in a highly efficient manner for analysis and integrating with ERP and MES systems. As shown in Figure 37, five major operations are continuously supported by an RFID-enabled conveyor system. The machinery generates large amounts of complex data that make analysis challenging. Data generated from the machinery are further used in analysis, integration, validation and visualisation using the advanced technologies of ML and CC.

For material allocation and diversion to the respective stations, raw fabrics are embedded with tracking technology, such as RFID tags. An RFID-enabled conveyor system facilitates the delivery of materials to the appropriate location. Material tracking is conducted by three unique items, namely, product ID (generated by the ERP system), item codes and batch IDs. These data are validated in the MES system at every stage of the manufacturing. From the beginning of the manufacturing, fabric rolls to be sleeved onto packed mattress protectors, and an enormous amount of data are generated. The collected data must undergo several pre-processing steps, as discussed in earlier sections of the chapter. The data require definition, validation and recognition. The collected data will contain many instances in which the manufacturing stopped for unknown reasons. Out of those unknown reasons, one definite answer is that anomalies exist within the data sets. Detecting these anomalies in high-dimensional data is necessary to overcome inconsistencies on the manufacturing line. The results of the AD and the correlation between the individual data was outlined.

## 5.5 Analysis of Machine Learning Algorithms

Before discussing the results, it is necessary to first understand the correlation between the data points. Data points were collected were from multiple industrial sensors, such as a temperature sensor, proximity sensor, accelerometer, pressure sensor, infrared sensor, tension sensor, ammeter, voltmeter, humidity sensor and light-dependent sensor. These sensors were independent in nature or were not directly related to each other. Any variation in any of the sensor inputs did not influence the other sensor readings. The power consumption reading was recorded to develop a correlation between the data points. A relationship between input variables and target variables is called a 'correlation'.

The power data variation was the direct result, or the target variable recorded from any of the operations failures. Failure data or event data can be traced back to the original cause of the interruption. Whenever there was an issue with the temperature of the machine, the machine stopped. To detect the event cause of this, the power consumption was colinearly matched. Correlation analysis is crucial to ensuring that there is a strong relationship between the data points. Once the correlation analysis is complete, the target variable is plotted or predicted in the given context. To define the correlation, when one of data variable begins to increase or decrease, the other variable also shows behavioural changes. There can be a positive linear change, a negative linear change or no linear change at all. There are many ways to calculate correlation coefficients, such as the Pearson correlation measure, the Spearman's rank correlation measure and the Kendall correlation measure.

Once the correlation coefficient has been identified, it is important to reduce the dimensionality of the data. As the data are high dimensional and high volume, predicting the target variable is problematic due to the high computational cost, model behaviour changes from training data to test data and because the distance between two data points becomes equal due to the high distribution of the data sets. To overcome these challenges, the dimensions of the data points can be reduced to focus on every data point, which makes it easier to focus on major events and behavioural changes.

### 5.5.1 Isolation Forest

The reason for the invention or advantage of IF-based AD is that it does not follow a regular method of detecting anomalies by profiling the normal data sets (Chun-Hui, Chen, Cong-Xiao, & Xing, 2018). Rather, it focuses directly on detecting the anomalies using the basic principle of decision trees. In this method, the tree partitions are made by the feature definition that the user defines (Elnour, Meskin, Khan, & Jain, 2020). Once the features are defined, the random split value in between the maximum and minimum value of the selected feature is selected. Focusing on the principle of the algorithm achieves the target values or anomalies using a smaller number of splits. Anomalies are generally identified with low numbers within data analysed and when graphically plotted these tend to fall outside the norms (Y. Huang, Xue, Su, & Han, 2020). Random splits or partitioning generate shorter paths to the anomalies compared with distinguishing them from normal data points. IF is an algorithm varied with its unique characteristics (e.g.: model based, density of the data points based, and data profiling based). The properties of IF include:

i) Sub-sampling. As the name suggest, sub-sampling does not have to isolate all the data points. It can easily ignore normal data points or the majority of data points. This increases the computing powers of the algorithm and leads to better predictions.

ii) Swamping. Swamping refers to when the normal data points lie very close to anomalies, and the model must separate the data points in multiple partitions in a process called ‘swamping’. The IF often chooses sub-sampling as the reduction method to reduce the swamping process.

iii) Masking. Masking is similar to swamping but only applies when the number of anomalies is high. When there are high number of anomalies present in a data set, identifying them is difficult. When this is the case, IF chooses masking to alleviate the number of data points within the data set using sub-sampling.

iv) High-dimensional data. The reason behind for IF as the key solution to HD data is that the data points in HD are equally distributed over the region. This makes it hard for traditional algorithms to identify anomalies. This does not mean that IF can easily detect anomalies within a data set; however, it can be improved by adding feature selection properties to the data set.

IF-based AD is built with two main steps. The first involves building isolation trees, as explained in the above model iterations. The second requires a proper anomaly rating to be generated after passing the test data instances through isolation trees. The anomaly score can be identified using the below algorithm.

### 5.5.1.1 Anomaly score

The anomaly score is calculated by comparing the data point observations of the isolation trees to the binary search trees. The algorithm terminates only when the external code isolation tree does not correspond to successful binary search trees. To illustrate this, the estimated average of h(x)}h(x) for a peripheral node breaks the unsuccessful search generated by binary search trees, as shown in Equation 1.

$$c(m) = \begin{cases} 2H(m-1) - \frac{2(m-1)}{n} & for\ m > 2 \\ 1 & for\ m = 2 \\ 0 & otherwise \end{cases} \cdots\cdots\cdots\cdots\cdots\cdots \textbf{Equation 1}$$

where $n$ is the testing data size, $m$ is the size of the sample set and $H$ is the harmonic number estimated by $H(i) = \ln(i) + \gamma$, where $\gamma$ is 0.5772156649 is the Euler–Mascheroni constant.

## 5.5.2 KNN Algorithm

The K-nearest neighbour (KNN) is an effective, simple, linear and non-parametric supervised type of ML algorithm. In relation to AD, the KNN chooses the unsupervised method (W. Jia, Yang, & Tong, 2010). This algorithm is used in regression models and classification models. The output clearly depends on the input variables. However, irrespective of inputs, the KNN works on a simple strategy (i.e., the closest lying data points are considered in the training set) (Pajouh, Javidan, Khayami, Dehghantanha, & Choo, 2019). Further, the result of classifying the KNN is always highly voted by neighbouring data points, whereas in a regression model, the result is obtained from the average of the nearest lying neighbours.

The KNN assumes that the nearest lying data points are the normal data sets, and it extracts the features of the neighbours (M. Zhou, Zhou, & Wen, 2016). The model predicts the closest neighbours depending on the proximity of the data points. The KNN algorithm works according to the following steps: i) loading the data, ii) initialising the nearest neighbours as the chosen ones for the feature extraction, iii) calculating the proximity distance between the training data set and the test data set, iv) extracting the proximity distance and index of the data points, v) sorting the features or test data sets in ascending order, vi) selecting the initial K elements from the sorted data, vii) labelling the data points for selected K elements and viii) deciding whether to return the classification or regression results depending on the mean or mode of the data points.

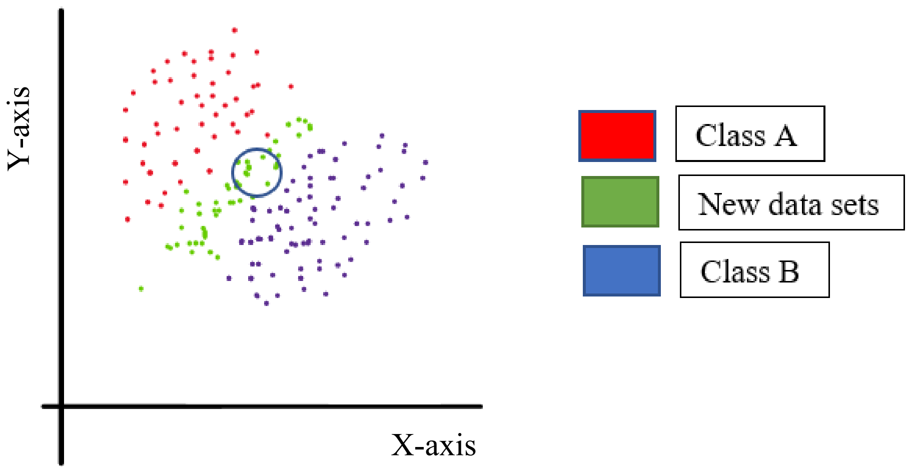



**Figure 37 KNN algorithm presentation**

The distance or proximity between two data points represents the similarity that completely originates from the denoted features. Thus, the Euclidean distance used in KNN can be derived from Equation 3:

$$dist(X,Y) = \sqrt{(x1-y1)^2 + (x2-y2)^2 + \cdots + (xn-yn)^2} \text{...............Equation 2}$$

The most important limitation of these distance-measuring equations is the similarity measure. The similarity measure means treating the nearest neighbours equally or extracting features of the data points equally. Equal extraction results in a miscalculation of normal data points and anomalous data points. Due to this, deciding on the extraction of features of data points creates ambiguity within the kinds of classification. Therefore, deciding on which feature is more important or impactful is uncertain.

## 5.6 Self-learning Algorithmic Efficiency Gains

Self-learning models were developed for the specific purpose of manufacturing. These models are not limited to any industry, as they are data oriented. Across the world, industries are beginning to understand the necessity of self-learning for growth. In the manufacturing industry, machinery is becoming smart and capable of self-learning. The data generated by machines has promising utility. Every day, enormous amounts of data that require high-end computing are produced by machines. This computing has resulted in promising efficiency gains in the manufacturing industry. Readily available software discussed in this research, such as MES and ERP, can compute these data. However, the resource planner and production planner were not integrated in the real-time scenario. Due to the lack of integration, the smart system did not produce the expected results in terms of efficiency.

The framework introduced in this research covered every aspect of integration and development. A large volume of data was considered when validating the framework, including interdepartmental data, production data and management data. The large volume of data generated created challenges when consolidating the framework operations.

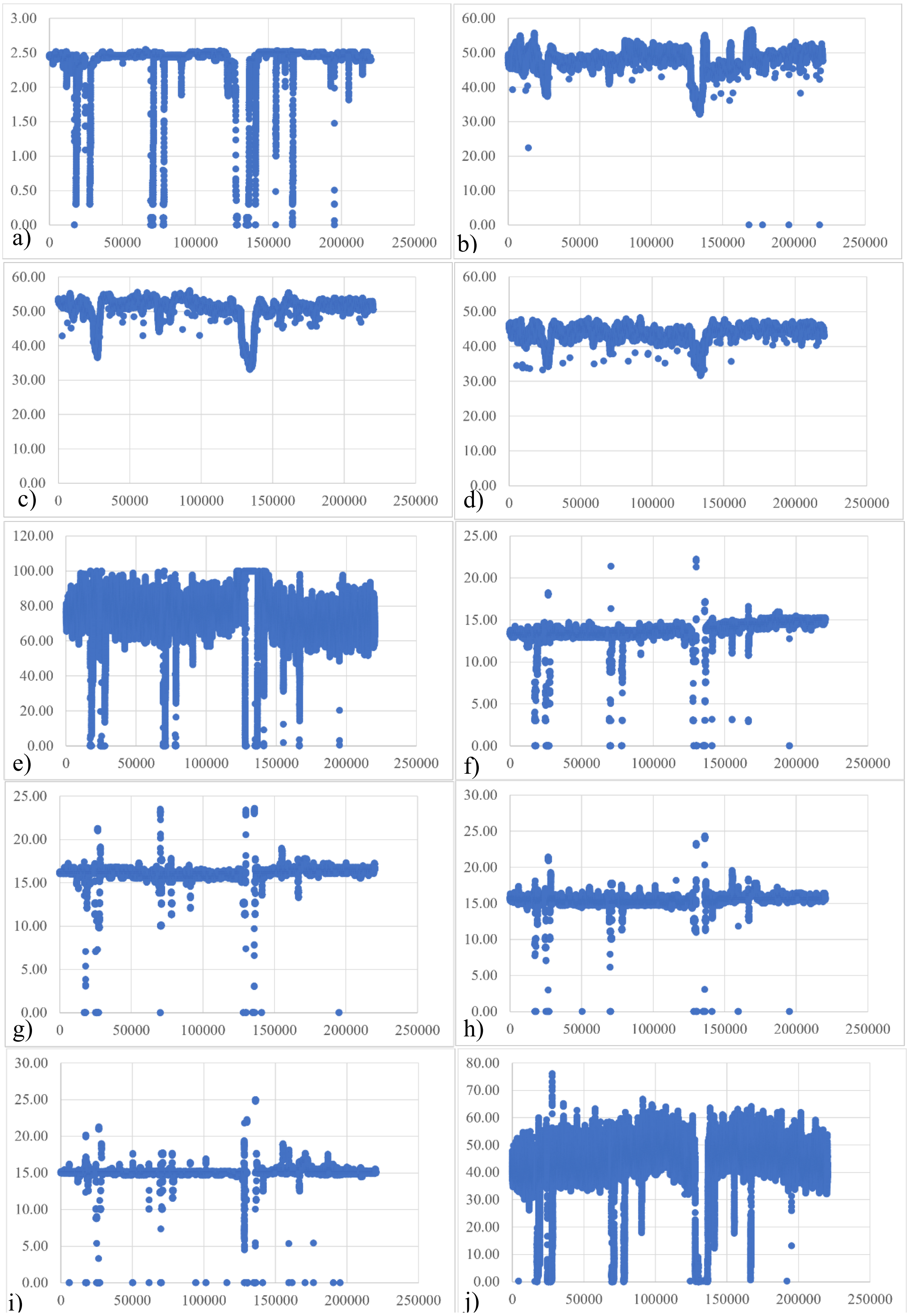
### 5.6.1 Event Failure Detection for Seamless Manufacturing

ML algorithms have been implemented within manufacturing for a decade. The challenges associated with implementing algorithms, such as complexity, high dimensionality, unscalable data and anarchic behaviour are ongoing. Implementing self-learning algorithms has resulted in improving on the dimensionality reduction of the data frame, the detection of event failures beforehand, improving maintenance scheduling and increases in uninterrupted manufacturing.

Data collected from machinery in the present case study were high dimensional, as shown in Figure 39. The data set presentation in the case study contained 13 different data points collected from a temperature sensor, proximity sensor, accelerometer, pressure sensor, infrared sensor, tension sensor, ammeter, voltmeter, humidity sensor and light-dependent sensor, along with real power, apparent power and voltage. This sensory information was collected from a sewing machine. The sensors were installed, and readings were recorded over a period of time.

**Table 16 High-dimensional data collection**

| timestamp | sensor_00 | sensor_01 | sensor_02 | sensor_03 | sensor_04 | sensor_05 | sensor_06 | sensor_07 | sensor_08 | sensor_9 | Real power |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **1/02/2021 0:00** | 2.47 | 47.09 | 53.21 | 46.31 | 76.46 | 13.41 | 16.13 | 15.57 | 15.05 | 37.23 | 42.18 |
| **1/02/2021 0:01** | 2.47 | 47.09 | 53.21 | 46.31 | 76.46 | 13.41 | 16.13 | 15.57 | 15.05 | 37.23 | 42.93 |
| **1/02/2021 0:02** | 2.44 | 47.35 | 53.21 | 46.40 | 73.55 | 13.32 | 16.04 | 15.62 | 15.01 | 37.87 | 41.79 |
| **1/02/2021 0:03** | 2.46 | 47.09 | 53.17 | 46.40 | 76.99 | 13.32 | 16.25 | 15.70 | 15.08 | 38.58 | 41.53 |
| **1/02/2021 0:04** | 2.45 | 47.14 | 53.21 | 46.40 | 76.59 | 13.35 | 16.21 | 15.70 | 15.08 | 39.49 | 42.39 |
| **1/02/2021 0:05** | 2.45 | 47.09 | 53.17 | 46.40 | 78.19 | 13.41 | 16.17 | 15.89 | 15.16 | 39.29 | 41.37 |
| **1/02/2021 0:06** | 2.46 | 47.05 | 53.17 | 46.40 | 75.82 | 13.43 | 16.13 | 15.65 | 15.08 | 38.30 | 41.3 |
| **1/02/2021 0:07** | 2.45 | 47.14 | 53.17 | 46.40 | 75.77 | 13.25 | 16.12 | 16.20 | 15.08 | 37.34 | 41.9 |
| **1/02/2021 0:08** | 2.46 | 47.09 | 53.17 | 46.40 | 74.59 | 13.29 | 16.13 | 15.47 | 15.12 | 38.45 | 41.91 |
| **1/02/2021 0:09** | 2.45 | 47.18 | 53.17 | 46.40 | 74.57 | 13.38 | 16.25 | 15.62 | 15.12 | 39.52 | 42.53 |
| **1/02/2021 0:10** | 2.46 | 47.48 | 53.13 | 46.40 | 76.05 | 13.41 | 16.17 | 15.65 | 15.12 | 39.90 | 59.7 |
| **1/02/2021 0:11** | 2.44 | 47.92 | 53.17 | 46.40 | 74.59 | 13.41 | 16.17 | 15.85 | 15.12 | 39.79 | 38.95 |
| **1/02/2021 0:12** | 2.46 | 48.26 | 53.13 | 46.40 | 76.96 | 13.35 | 16.17 | 15.73 | 15.01 | 40.04 | 40.93 |
| **1/02/2021 0:13** | 2.45 | 48.44 | 53.17 | 46.40 | 75.67 | 13.32 | 16.17 | 15.85 | 15.17 | 40.90 | 42.25 |
| **1/02/2021 0:14** | 2.45 | 48.57 | 53.17 | 46.40 | 80.66 | 13.39 | 16.13 | 15.53 | 15.09 | 41.83 | 42.55 |
| **1/02/2021 0:15** | 2.46 | 48.39 | 53.13 | 46.40 | 78.13 | 13.35 | 16.21 | 15.45 | 15.13 | 43.13 | 42.59 |
| **1/02/2021 0:16** | 2.45 | 48.39 | 53.17 | 46.31 | 77.89 | 13.30 | 16.17 | 15.89 | 15.08 | 43.60 | 42.07 |
| **1/02/2021 0:17** | 2.46 | 48.48 | 53.69 | 46.31 | 77.31 | 13.35 | 16.17 | 15.62 | 15.01 | 43.86 | 42.06 |
| **1/02/2021 0:18** | 2.45 | 48.61 | 53.13 | 46.31 | 76.66 | 13.35 | 16.21 | 15.81 | 15.05 | 43.36 | 42.11 |
| **1/02/2021 0:19** | 2.46 | 48.61 | 53.17 | 46.31 | 78.49 | 13.35 | 16.13 | 15.70 | 15.08 | 42.28 | 42.12 |
| **1/02/2021 0:20** | 2.45 | 49.09 | 53.04 | 46.31 | 76.96 | 13.35 | 16.17 | 15.77 | 15.12 | 42.13 | 42.36 |
| **1/02/2021 0:21** | 2.46 | 49.22 | 53.13 | 46.31 | 78.76 | 13.35 | 16.17 | 15.45 | 15.12 | 41.95 | 47.8 |
| **1/02/2021 0:22** | 2.45 | 48.78 | 53.13 | 46.27 | 76.26 | 13.41 | 16.21 | 15.65 | 15.08 | 42.94 | 52.98 |
| **1/02/2021 0:23** | 2.45 | 49.09 | 53.17 | 46.27 | 79.25 | 13.35 | 16.21 | 15.81 | 15.08 | 44.51 | 42.45 |
| **1/02/2021 0:24** | 2.45 | 49.22 | 53.04 | 46.27 | 76.89 | 13.32 | 16.12 | 15.78 | 15.05 | 45.31 | 89.71 |



**a) sensor_00, b) sensor_01, c) sensor_02, d) sensor_03, e) sensor_04, f) sensor_05, g) sensor_06, h) sensor_07, i) sensor_08, and j) sensor_09.**

The data collected contained many problems, such as null values, inconsistencies and event failures. The basic problem affecting the data was that all 10 sensors other than the power parameters were independent data variables. Detecting individual sensor failure was simple; however, detecting event failures in all sensors at the same time was highly challenging. Figure 38 shows the data distribution for all the sensors fitted to the machine. As shown, some data points lay outside the normal data points, though they were rare and infrequent. Self-learning algorithms were used to detect failures and maintain efficiency during manufacturing.

Initially, the aim was to reduce the dimensionality of the data frame. There are many proven dimensionality reduction techniques. Principal component analysis was used to reduce the dimensionality of the data. Further, the collected data were synthesised to add more complexity and dimensionalities. This ensured ML to adopt and self-learn for any unknowns (e.g.: future predictions) as shown in Figures 39 and 40. Once the data were contained a greater number of event failures, multiple AD techniques were implemented. Out of these, IF and KNN were the best-performing algorithms. The performance metrics of these techniques was evaluated, as depicted in Figure 40. IF showed a 98% accuracy compared with other techniques used in the manufacturing data scenario, as shown in Figures 41, 42 and 43.

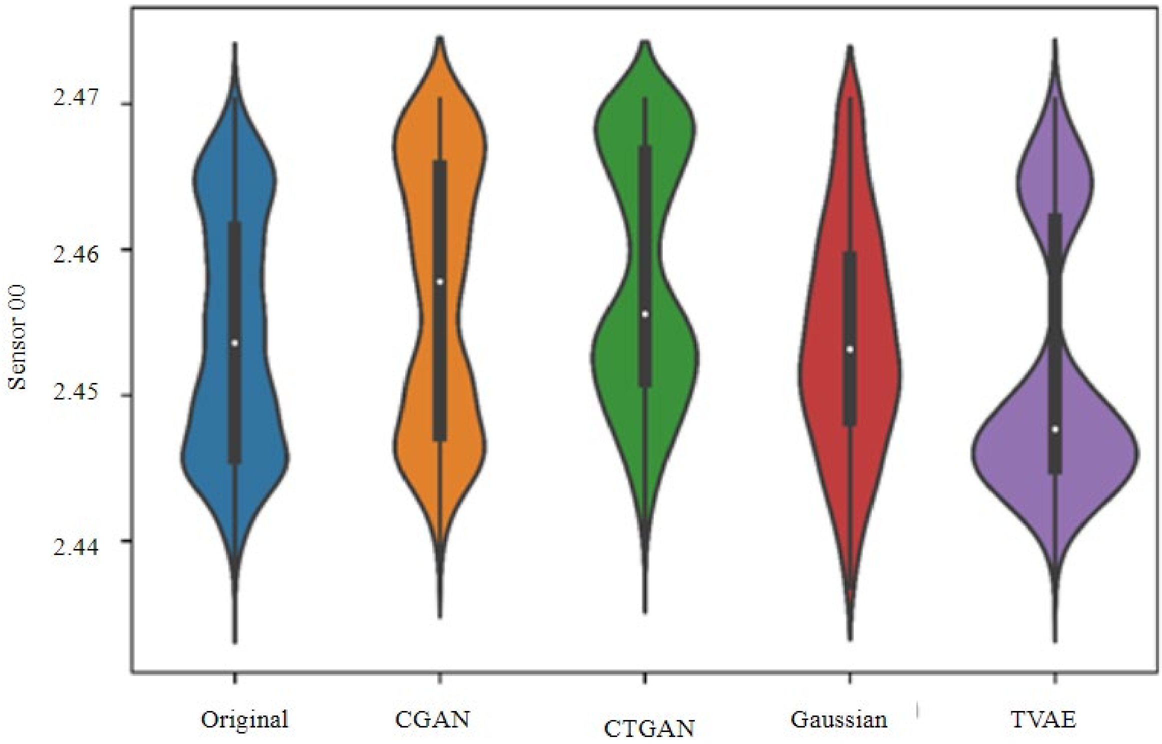



**Figure 39 Sensor_00 synthesis**

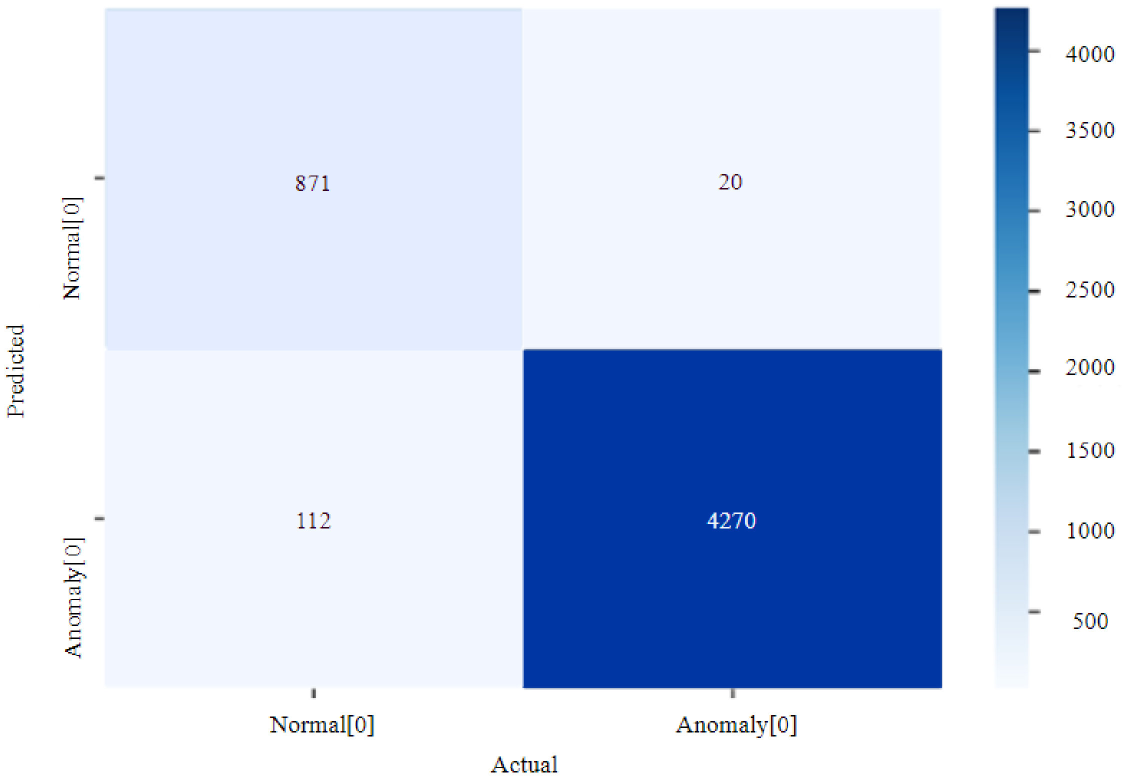



**Figure 40 Isolation forest data distribution with anomalies**

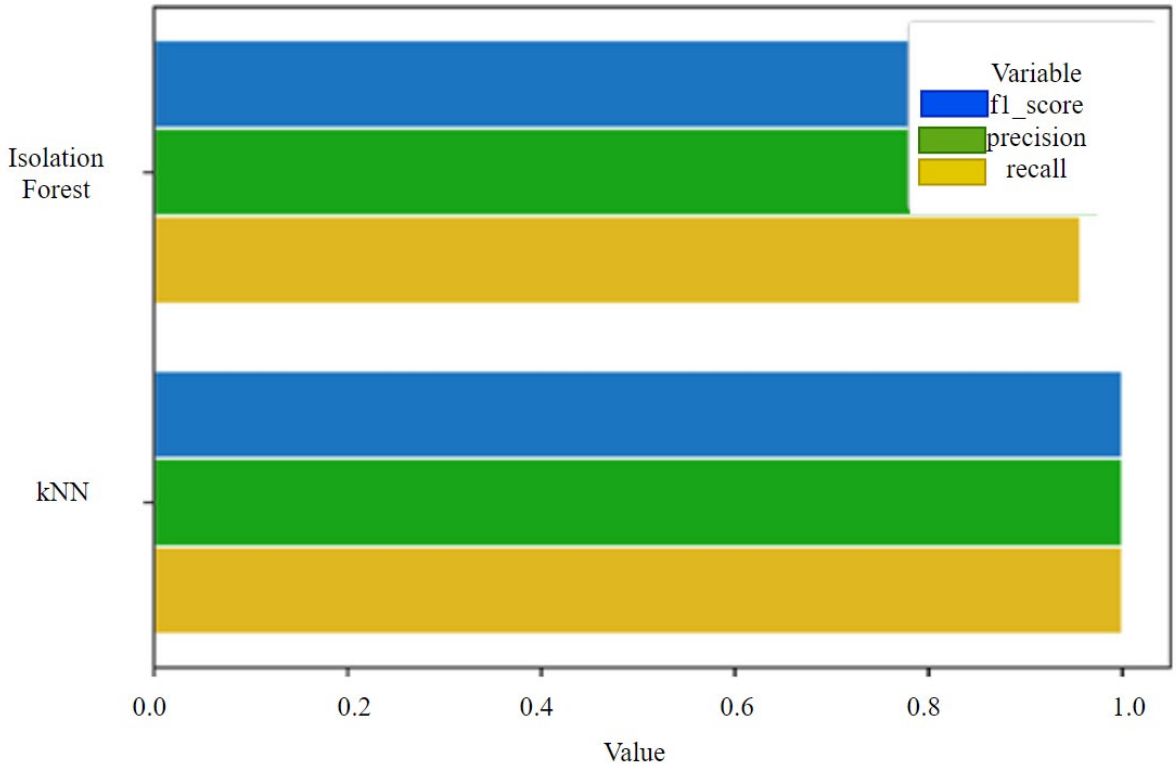



**Figure 41 Performance metrics comparison**

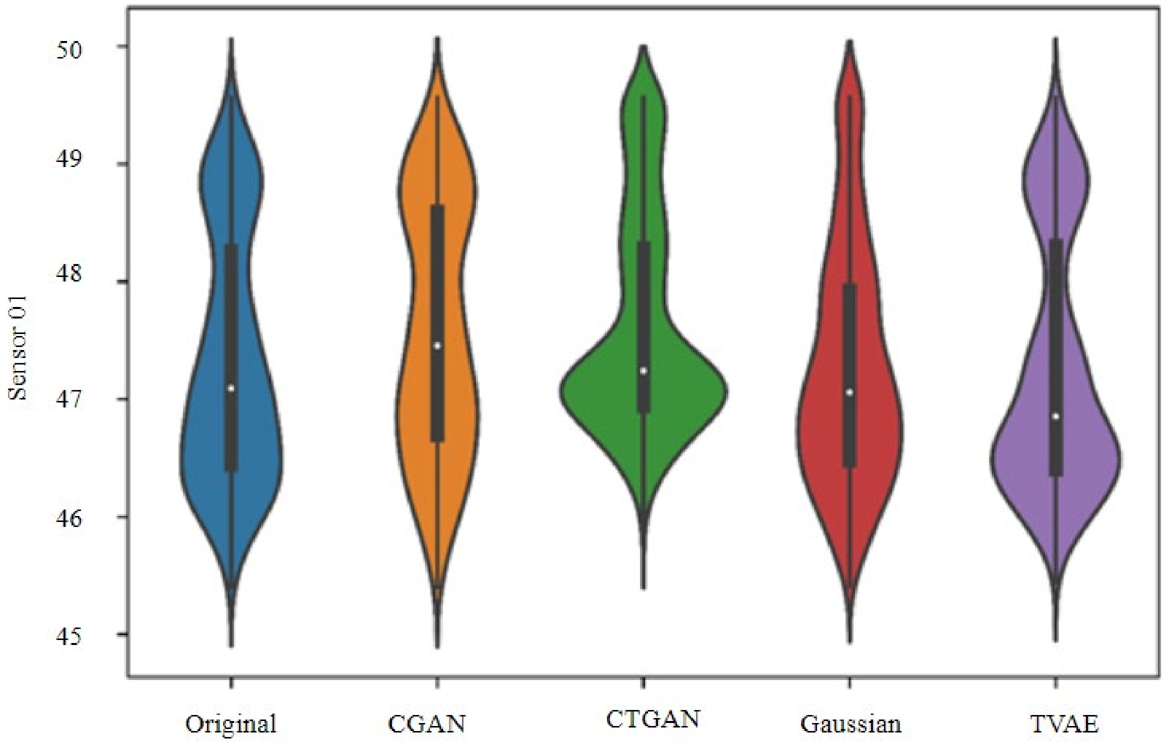



**Figure 42 Sensor 01 data synthesis**

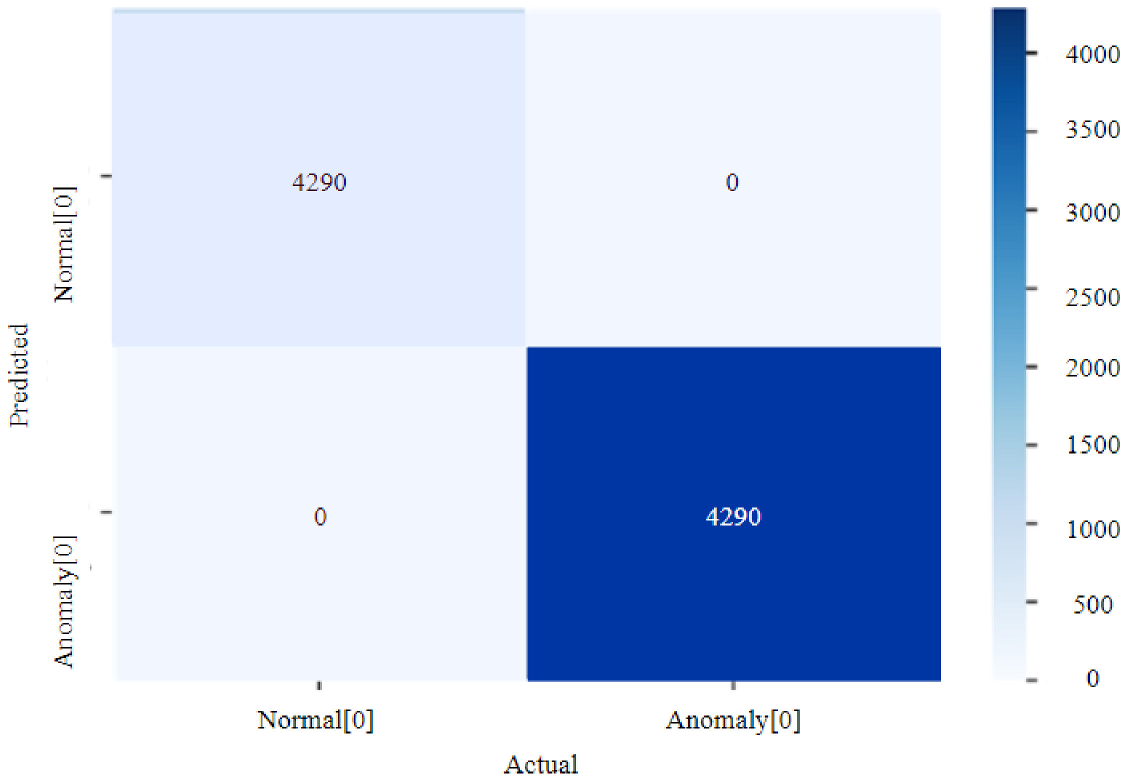



**Figure 43 KNN algorithm anomaly detection**

## 5.6.2 Takt Efficiency Enhancements

Once the AD techniques had been applied to the data sets and recommendations fed back into the system, the system performed comparatively better. The comparison between the traditional and SM framework was validated and was shown to perform 30% better compared with the traditional system. Figure 44 shows that the traditional system had higher process times that were nearly 60 seconds per product process time. However, compared with the SM framework, the implemented system has an approximately ~43 seconds process time. The difference in these processing times resulted in the production of a greater number of products in the same amount of time. This increase in the production rate directly resulted from the seamless and highly efficient manufacturing system.

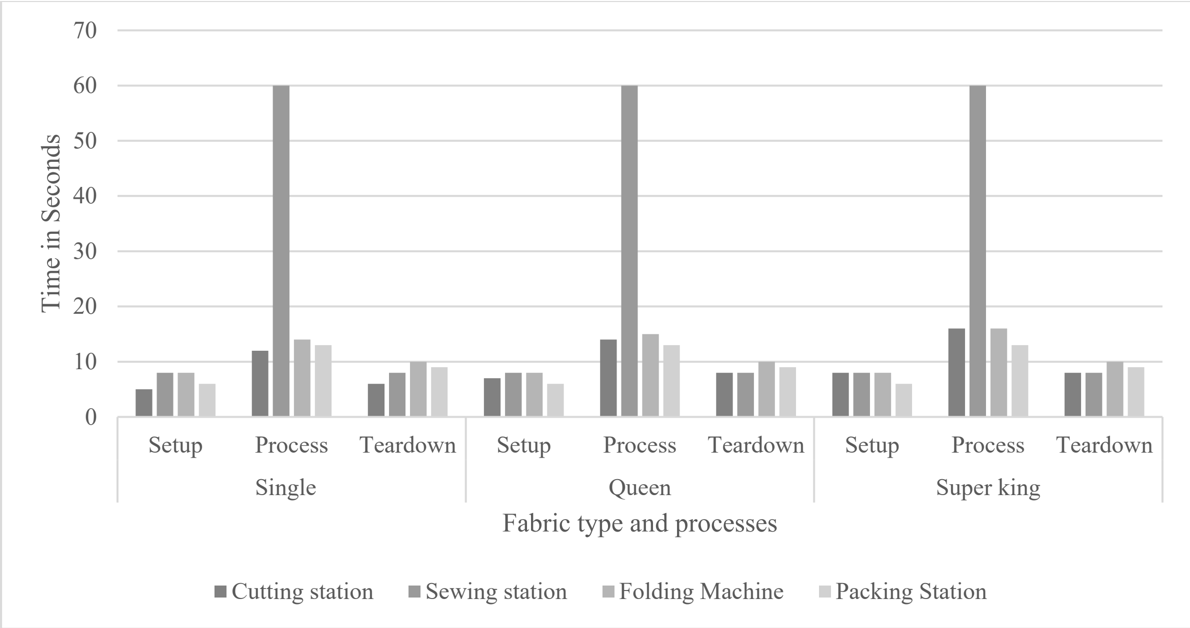



**Figure 44 Traditional framework takt analysis**

The framework implemented improved the feasibility of the intrinsic natured manufacturing. The machines produced complex, unscalable and untraceable data. The AD algorithms that were built to be self-learning showed that the data generated by these machines could be used to increase efficiency. As shown in Figure 46, there was a 30% efficiency gain in terms of the time required to manufacture one unit of textile.

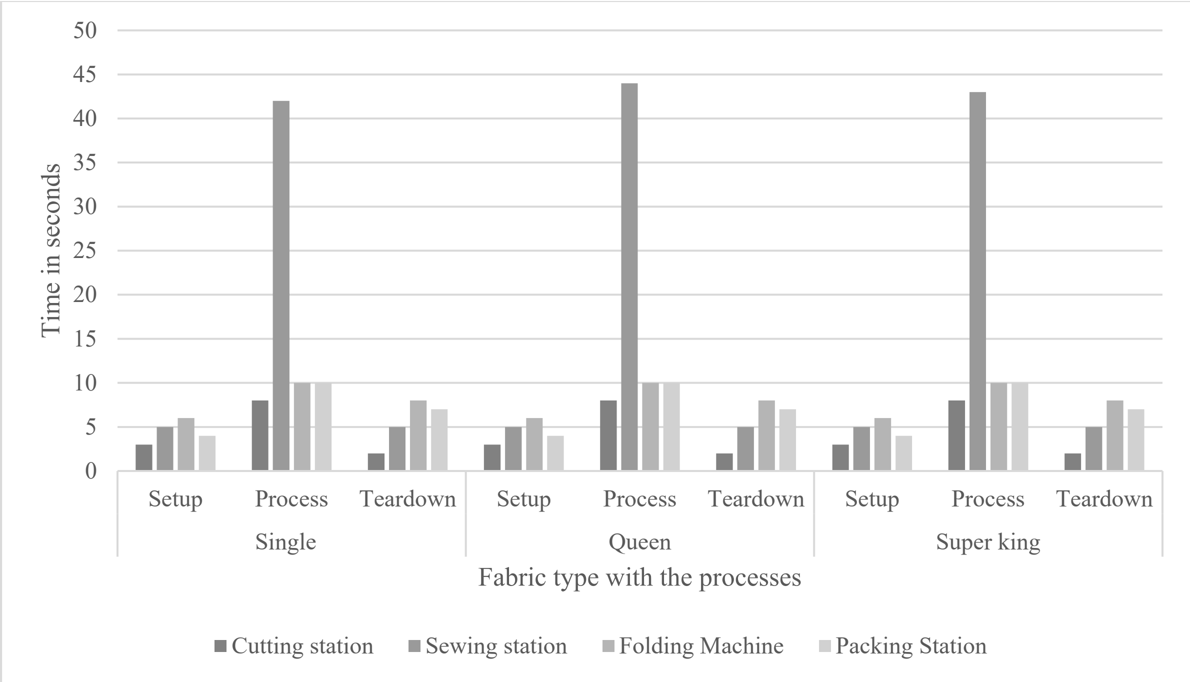



**Figure 45 Smart manufacturing framework takt analysis**

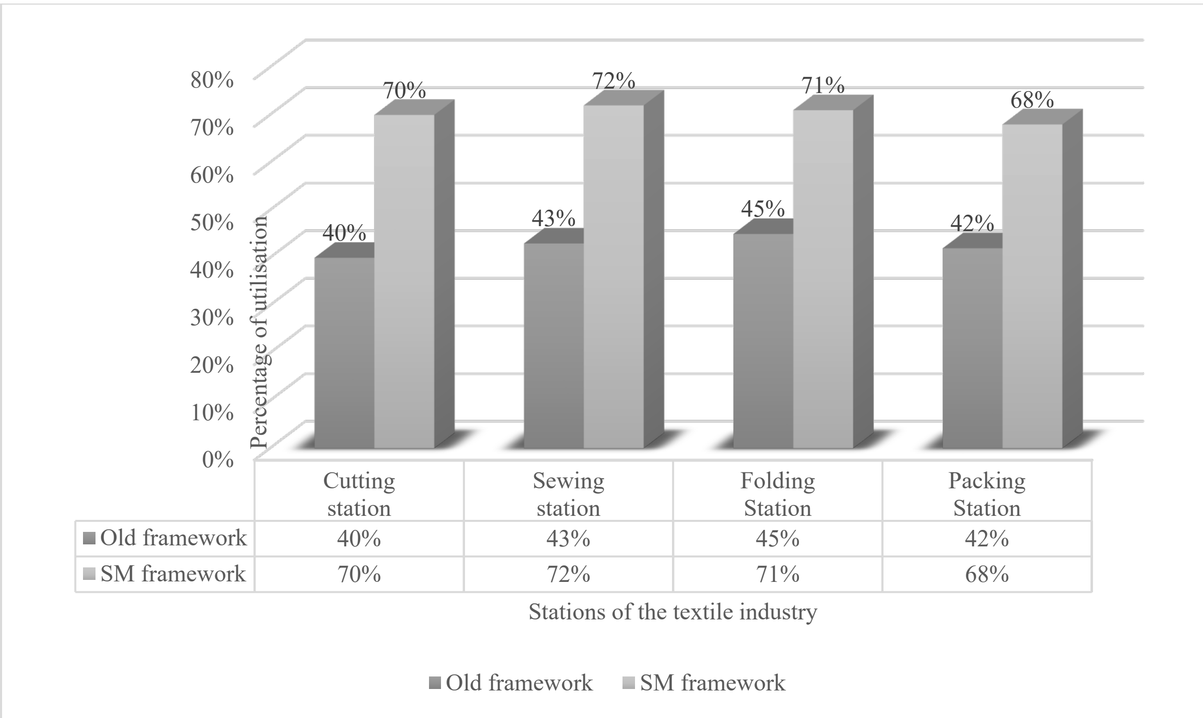



**Figure 46 Framework utilisation comparison**

## 5.7 Chapter Summary

The three Vs of data—volume, variety and velocity—play an important role in determining the characteristics of the manufacturing sector. Enormous and ever-increasing amounts of dynamically changing data are generated in the manufacturing industry. The data generated and analysed in the case study were used to increase the efficiency of the manufacturing line. This chapter discussed the cloud-centric SM paradigm, which is powered by data generated by the manufacturing system. This paradigm has multiple dimensions of perception. This chapter developed and analysed the optimal solution, covering the historical aspects and data-generation stage, including maintenance aspects with cloud-empowered manufacturing. In the data generation stage, the development of the model was vital. This included generation, transmission, processing and realisation. In the development stage, the cloud systems enabled data-centric integration and administrative functions. Lastly, fault detection and correction factors were automated in a real-time application aided by AD in the cloud. Below is a summary of the chapter:

i) When outlining the possibilities of the smart system, this chapter illustrated the many challenges involves at every stage of development, including current trends in data collection, pre-processing and realisation, particularly for high-dimensional data with limited commercial success. The main reasons for limited commercial success were the lack of know-how, the lack of a skilled workforce, affordability issues and the alliance and availability of integrated hardware–software interfacing. At present, a limited or singular adoption of cloud-centric manufacturing systems are seen with no integrated approaches. Although the cloud provides unique technical advantages (e.g., it can overcome low latency, network unavailability and server issues), a key research gap involves harnessing these benefits in an integrated manufacturing system.

ii) At present, an overarching SM system integrated with ERP is missing from the literature. Therefore, a complete manufacturing solution is lacking. A major contribution of this research is the provision of a nexus of a synergised cloud-centric SM system with intelligent data analytics. The SM comprises CPS, and integration is a major challenge. To date, no case studies have provided a complete integrated SM-based CPS validation in the manufacturing industry, and SM practices have seen partial implementation at singularities. Although SM has been developed theoretically, there have been few practical implementations in real-time integrated systems to address efficiency, decision-making and low-volume manufacturing. Thus, this research addressed this key gap with a cloud-centric SM framework. This framework used sensory technologies, encapsulating IoT gateways and IIoT-integrated systems to capture more heterogenous operational data from the manufacturing system.

iii) The HD data captured constituted 13 dimensions from 10 different sensors from various locations of the machine operation. Ten different sensors from the machines were captured using Raspberry Pi. These 10 sensors were independent sensors that provided independent HD data to be controlled and analysed. This control and analysis of the HD data, which predicted the machine behaviour, was challenging. The machine sensors outputted real-time HD data for control and analysis. The machine behaviour was controlled and predicted based on the analysis of these HD data.

iv) The HD data collected from the machine sensors was complex. This complexity was reduced by applying multiple methods, out of which principal component analysis was selected as the best of all other dimensional-reduction algorithms, as it targeted the maximum possible variance in the data set and projected in a smaller subspace. This method of dimensional reduction illuminated the underlying important features of the machine. Several different types of sensory data were analysed for AD. Sensor_00 and Sensor_01 were used to test the implementation of the ML algorithms for AD. The following algorithms for AD were tested: random forest, decision trees, SVM, multiple linear regression, IF and KNN. Of these techniques, IF and KNN were successful, with KNN outperforming IF by 96%.

v) Although the KNN algorithm showed superior performance compared with the IF algorithm, the IF algorithm was chosen for its ability to train unsupervised HD data. The KNN algorithm lacked the ability to train in an unsupervised manner. The AD technique involved analysing sensors for various HD data, thus tracing anomalous data sensor (e.g., real power values were detected from various HD data sensor). The detection technique involved inspecting all the data points (from all the sensor measurements) defined at the specific timestamp. Further, the IF algorithm detected anomalies based on the upper and lower thresholds of each sensor measurement. For example, the power consumption 1247th data sample in the dataset and relevant AD were presented for the sewing operation as a case study. Ten sensors were tested and gave the following readings: 2.440, 47.309, 52.127, 44.531, 77.184, 13.093, 16.168, 52.910, 15.119 and 39.726. Based on machine failures, Sensor_08 threshold was identified between 14.98 and 15.98. Hence, the IF algorithm identified and predicted failure as Sensor_08 for AD.

vi) In conclusion, implementing the ML and AD algorithms on manufacturing data resulted in an overall ~30% increase in efficiency. Cutting, sewing, folding and packing increased in efficacy by 30%, 29%, 26% and 26%, respectively. Data analytical programs or AD strategies illustrated in this research were shown to be feasible. The reasons for the failure of other algorithms or techniques should be explored in future work. The integration of these technologies in a real-time scenario is the most significant contribution of the present work, as this will enhance the system efficacy in predictive measures, preventive methods and adaptable systems.

# 6 Cloud-Centric Data-Driven Paradigm

This chapter consolidates the research outcomes of two major research problems: decision-making frameworks and low-volume manufacturing. These research problems were addressed by integrating advanced technologies, such as CPS and CC. Cost and time analyses of the earlier system compared with the new SM system are discussed in detail.

## 6.1 Introduction

Manufacturers around the world are trying to take advantage of advancements in technologies that integrate the physical and virtual shopfloor. Many theoretical approaches to integrated frameworks of digital technologies have been proposed. These integrated technologies are referred to in different ways around the world, such as Industry 4.0 in Germany, Made in China 2025 and Industrial Internet in the US (Leng et al., 2021; Tantawi, Fidan, & Tantawy, 2019). These terms refer to the application of digital technologies within complex manufacturing systems. SM is the framework or practice that has evolved using data acquired from machines on the physical shopfloor. The data generated throughout the product lifecycle can be analysed from multiple perspectives (Stojanovic et al., 2017).

Data generated by systems are unpredictable in terms of growth and are purely unrefined. The ability to make informed or precise decisions within manufacturing relies on manufacturing data. However, unfortunately, until now, decision-making frameworks have lacked efficiency (Wallis, Schillinger, Backmund, Reich, & Schindelhauer, 2020). This is because manufacturing systems have neglected the generated data. This has resulted in a loss of productivity, a lack of cost effectiveness and reduced flexibility in manufacturing. According to (Yao et al., 2017), more than 100 EB data are generated from manufacturing systems around the world annually. However, data-centric manufacturing is missing from existing systems. Implementing data-centric manufacturing systems has become an important aspect of SM practices, and research conducted on such systems has encouraged manufacturers to look closely at such approaches (Yao et al., 2017).

The collaboration of cloud empowerment in manufacturing systems should not be underestimated. Data-centric manufacturing appears promising, but the platform of data analytics is equally important. Many improvements and advancements have occurred in relation to the manufacturing industry. One such advancement is CC or cloud-empowered manufacturing systems (Tsai & Chang, 2018). The important contribution of cloud-empowered manufacturing is unmatched on-demand computing along with available, convenient and highly reliable services.

## 6.2 Cyber-Integrated Low-Volume Manufacturing

Low-volume individualised product manufacturing is a key constraint of the SM framework. The introduction and integration of CPS in the framework directly addresses low-volume individualised product manufacturing. The physical and virtual shopfloor was explained in the conceptual framework section of Chapter 4. The components of both these shopfloors were designed and simulated in CPS. Figures 47 and 48 show a virtual simulation of a manufacturing system with a real-time, tracking-enabled system. This real-time tracking helped the SM framework track the manufacturing line and gather data. Such data can help design flexible manufacturing systems, while pre-production simulations and real-time simulations provide accessibility.

The textile-industry manufacturer on which the case study was conducted had more than 1,800 footprints of products. The textile industry is a customer-oriented industry, and every individual customer has specific needs and desires in relation to the products they buy. Manufacturing a wide variety of products in a limited time is challenging. To meet market expectations, industries must maintain stocks of up to six months. Maintaining six months' worth of stock necessitates undesirable and resource-hungry procedures, such as warehousing, management and tracking systems. In addition, when stock is kept for long periods, there can be issues of a decline in quality, pests, bugs and other problems.

The SM system takes information from the integrated ERP and MES system with the manufacturing and resource data. This information is provided for CPS to design the pre-manufacturing simulation that results in a better understanding of the manufacturing cycle. This anytime, anywhere information leads to the transformation of traditional practices to advanced manufacturing. As CPS is also powered by CC, the operations that are performed in real time are handled and executed in a hassle-free manner. The pilot test showed that CPS could be integrated into the proposed SM framework. Due to the pre-manufacturing simulation status of inventory, orders and supplier data was visualised before manufacturing. The major characteristics of low-volume manufacturing are low yearly production volumes, high complexity and high variety, high cost and customisability.

The aforementioned characteristics of low-volume products lead the following problems:

i) complete make-to-order production policies

ii) a high level of manual work

iii) the use of universal production equipment

iv) the sharing of production resources among different products.

The same characteristics also influence the product introduction process, which exhibits the following characteristics:

i) few engineering prototypes

ii) a limited and uncertain number of pre-series productions

iii) the infeasibility of conventional production ramp-up

iv) the modification of existing products rather than the development of new products

v) the use of existing production systems with slight modifications for new products

vi) the high frequency of introduction of new products.

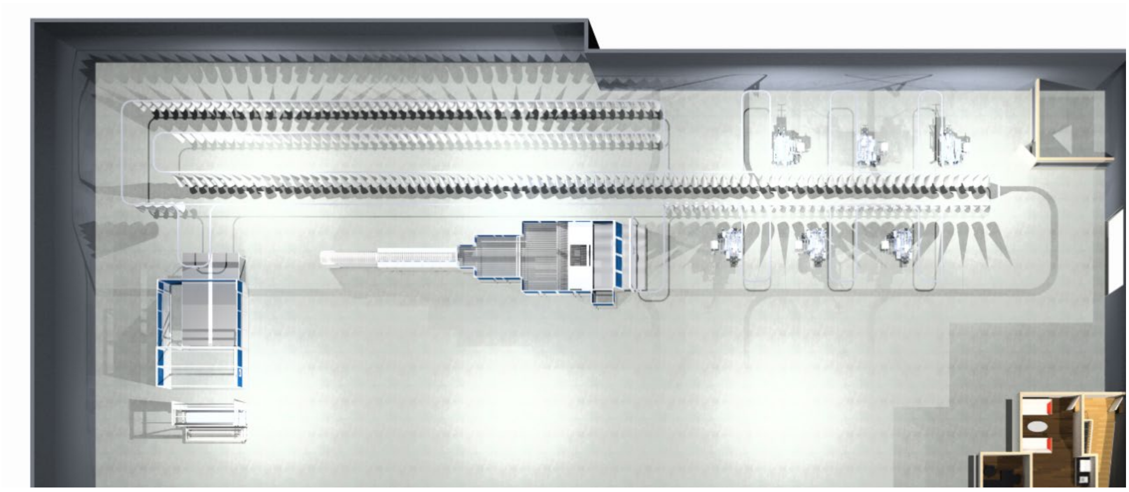


**Figure 47 Cyber physical system–enabled smart manufacturing**

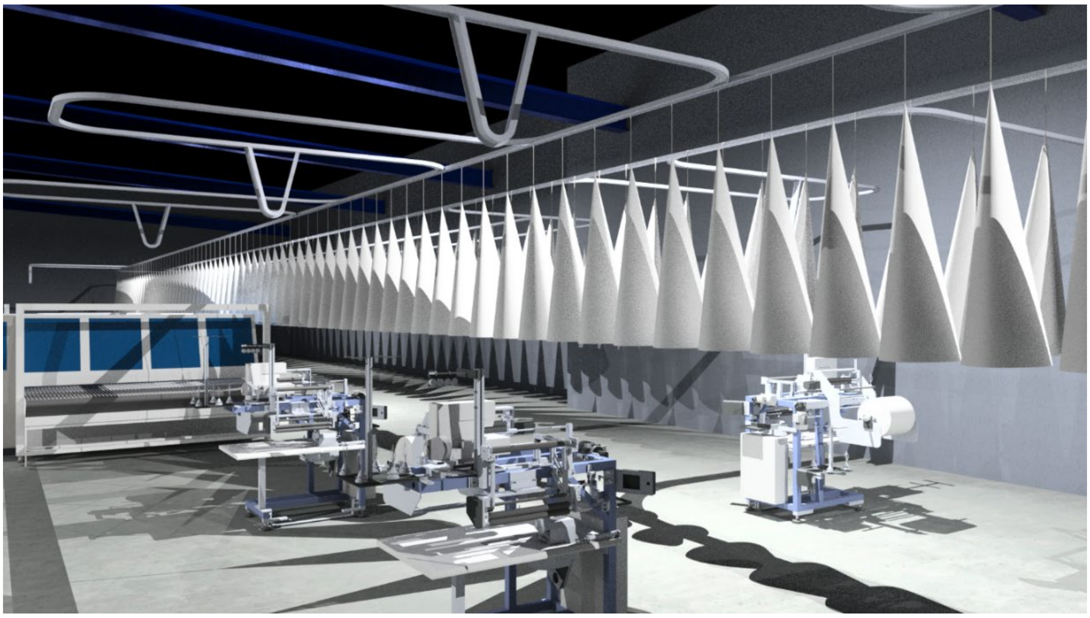


**Figure 48 Isometric view of a smart manufacturing system**

## 6.3 Smart Manufacturing Flow

The illustration in Figure 49, shows the flow of products and information and offers an overview of connectivity. Siemens offers various solutions for implementing an SM-like system on its MindSphere platform. The SM server consists of the local deployment of MindSphere along with connectivity tools, an instance of NetSuite ERP Solution and manufacturing simulation software. Most of the equipment is equipped with industrial PLC, which provides control and data-logging capabilities. All assets with PLCs are connected on an industrial local network, and data are fed into the SM server. Moving equipment and additional sensors, such as RFID sensors, uses a wireless network to communicate.

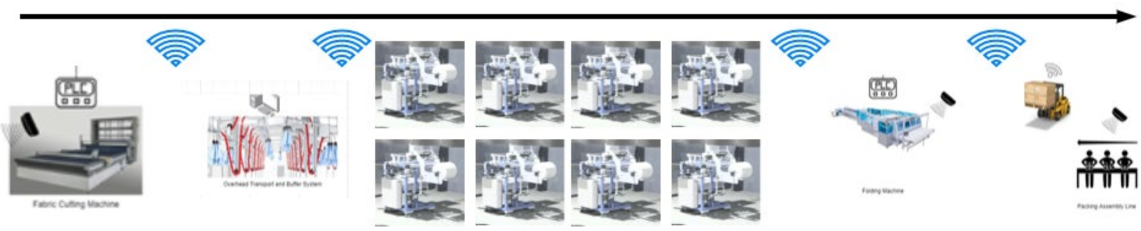



**Figure 49 Mattress protector production flow and communication overview**

Like MindSphere, the simulation software can access and use the PLC connectivity.

Therefore, it can simulate the entire shift and suggest machine parameters, job ordering and material requirements. The combination of these packages creates this sophisticated workflow in the manufacturing.

### 6.3.1 Production Flow

The design flow generated after studying the manufacturing line led to several recommendations. Out of many possibilities, the best fit and feasible solution for the production flow developed in this research(figure 50) was as follows:

i) On receiving a customer order, a work order is generated within the ERP system, and a production plan is created.
ii) MES retrieves the work order, and the simulation software generates the efficient machine parameters.
iii) Raw material information is sent to the forklift console with RFID sensors.
iv) Raw material is collected from the specified location, and the stock is updated simultaneously.
v) The forklift passes through a validation checkpoint with RFID sensors to check whether the correct material and quantity of material have been collected.
vi) The materials are loaded onto a storage carousel with material information.
vii) The machine parameters and processes are updated from the SM based on the simulation.
viii) During the cutting process, an Eton gripper collects the cut fabric and updates the system information with the product data.
ix) The Eton system buffers the cut fabric and distributes it to the correct sewing station, based on which a station is assigned with the product production.
x) On delivering the fabric to the sewing station, the RFID sensors verify whether the correct fabric has been delivered.
xi) An RFID is sewn in the product at the sewing station, and the RFID system updates the product information on the SM.
xii) The product continues on the Eton system to the folding machine, and RFID sensors detect the product and adjust the machine parameters.
xiii) On completion of folding, the product is moved onto the packing assembly line.

xiv) The product is placed on a conveyor to be taken to the correct packing station. On loading the folded fabric onto the conveyor, a metal detector checks the product, and an RFID sensor checks the product type to route it to the correct station.

xv) The final products are boxed and placed on pallets with embedded RFID labels. The forklift collects the pallet, and RFID sensors update the system with the pallet information, products on it and the location at which they are stored.

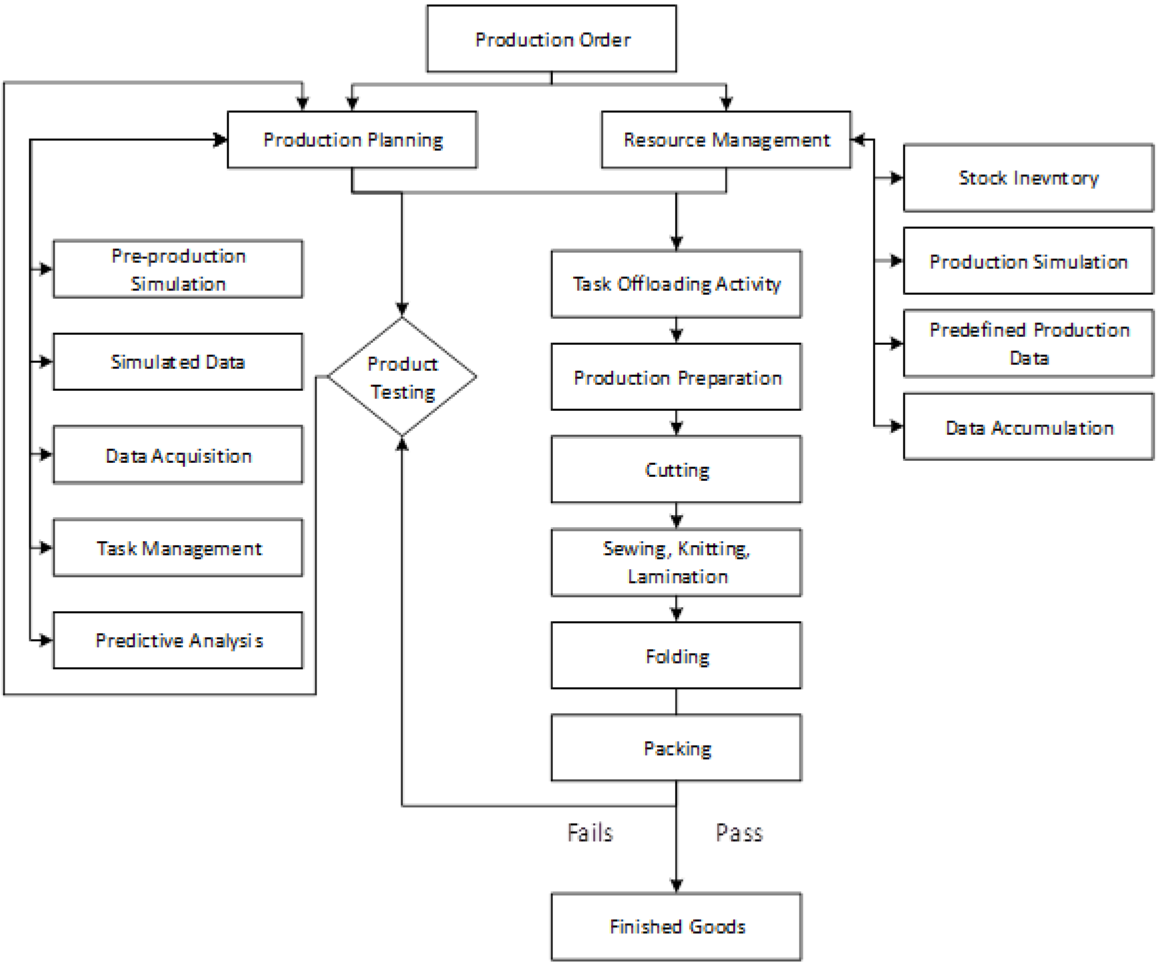



**Figure 50 Operational flow of SM**

## 6.4 Cloud Empowerment in Smart Manufacturing System

Cloud deployment and implementation has been conducted in many ways. There has been continuous development in the field of CC. However, ensuring the best solution and fit model that can be deployed within all scenarios is crucial. The below section details the requirements for CC.

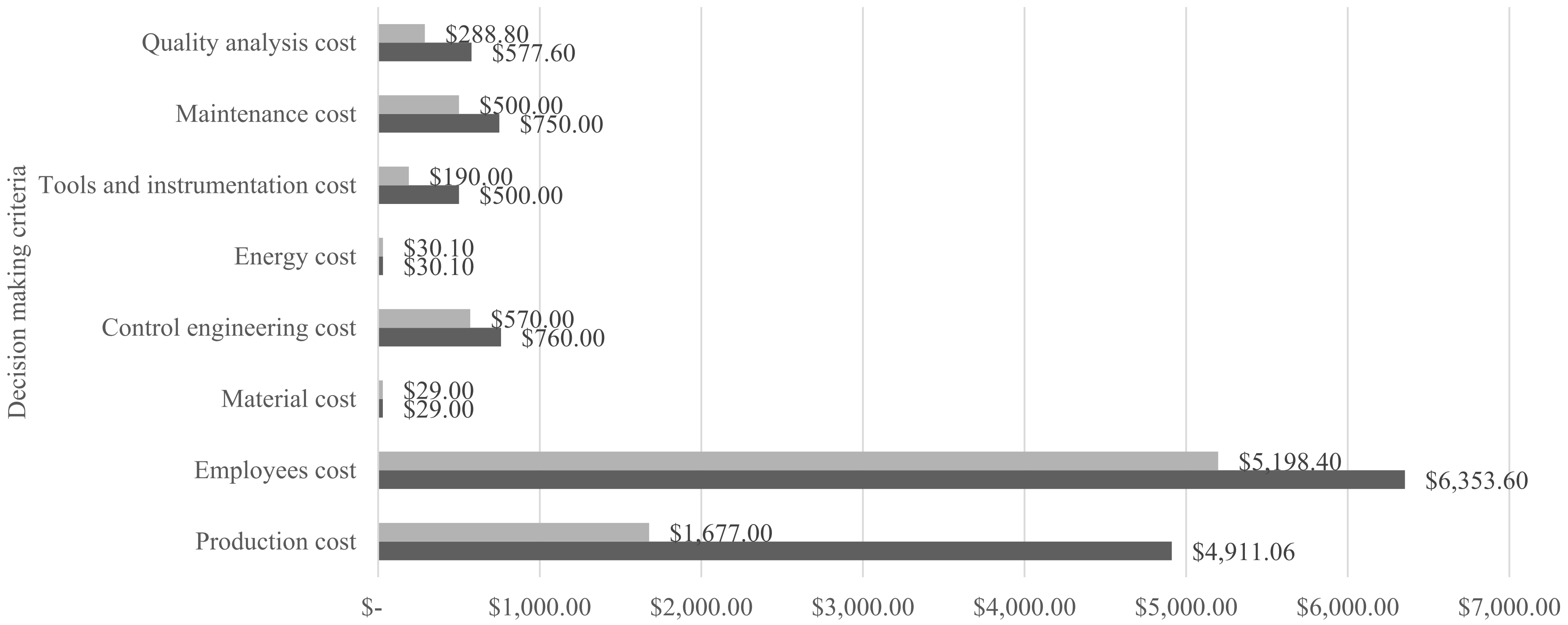
## 6.5 Requirements for Cloud Computing

As discussed in relation to data methods in the previous sections of this chapter, cloud empowerment within the system also plays a vital role. In CC, the process is treated as a service (e.g., anything as a service [XaaS], platform as a Service [PaaS], software as a service [SaaS] and infrastructure as a service [IaaS]). In CC, these services form a layered system. Processing, storage, networks and other essential computing resources are specified as standardised services via the network at the infrastructure layer. The clients of cloud providers can use their underlying infrastructure to deploy and operate OS systems and software. In the integrated-development environment, PaaS provides concepts and services for building, testing, implementing, hosting and managing applications. The application layer supports a full range of SaaS applications. All the underlying XaaS layers can be accessed through the UI layer at the top. This results in the evolution and merging of multiple computing developments (e.g., package delivery, pay-as-you-go/use, flexibility, virtualisation, interrupted computing, space and grid computing). The multidisciplinary research field of CC requires appropriate and versatile business and IT infrastructure that can address issues such as computational power, storage capacity and servers to run multiple instances. CC plays a dynamic role in the corporate field of manufacturing in which everything is outsourced to multinational companies around the globe when handling internal data and operations.

## 6.6 Cloud-Centred Systems for Improved Decision-Making Capabilities

Along with the implementation of self-learning algorithms and CPS in the manufacturing industry, decision-making capabilities have also improved. This improvement in decision-making frameworks has helped create a more economical and productive manufacturing industry. Sensitive information about the manufacturing industry that is often neglected is the introduction of variations within product portfolios. This is due to the fear of missing out on market opportunities or doubts about existing competition, particularly among SMEs.

In the present work, a cloud-centred decision-making framework was introduced to overcome these issues and create new opportunities for manufacturers, as well as to improve and support the product-introduction process in low-volume manufacturing, achieve shorter times to market/payback, with fewer production disturbances and higher product quality, while also identifying factors that affect the product introduction process. Therefore, this research identified the characteristics of low-volume products and production systems and studied their influences on the product-introduction process.




| | Production cost | Employees cost | Material cost | Control engineering cost | Energy cost | Tools and instrumentation cost | Maintenance cost | Quality analysis cost |
|---|---|---|---|---|---|---|---|---|
| SM framework | $1,677.00 | $5,198.40 | $29.00 | $570.00 | $30.10 | $190.00 | $500.00 | $288.80 |
| Existing framework | $4,911.06 | $6,353.60 | $29.00 | $760.00 | $30.10 | $500.00 | $750.00 | $577.60 |

Cost per day

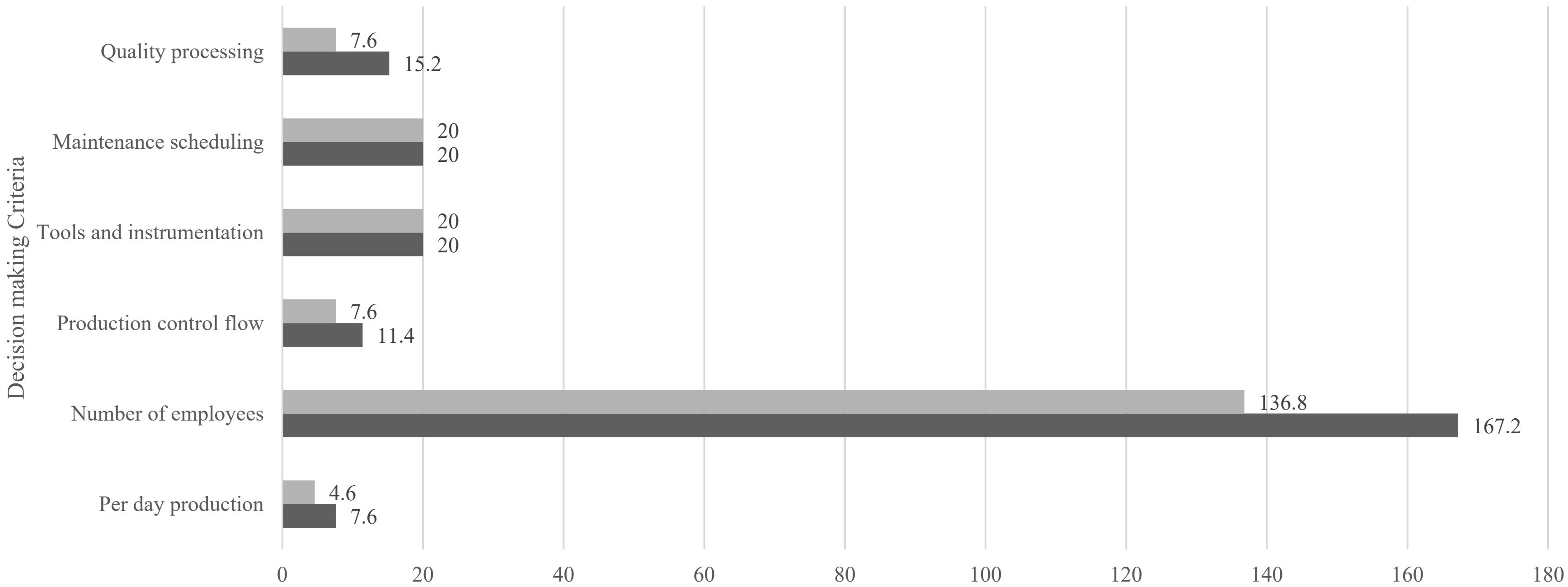
SM framework  Existing framework

**Figure 51 Cost savings from smart manufacturing**

The decision-making capabilities of SM were enhanced by implementing advanced technologies, such as CC and CPS. CC made the manufacturing data seamless and flawless. Similarly, CPS contributed to the preplanning production. Preplanning often contributes to the allocation of interdisciplinary departmental resources. The resources obtained from these departments were sorted, organised and managed at a single instance in the present work. Figure 50 shows the clear importance of and difference between traditional and SM frameworks. An average of an 18% difference in cost variation was identified. As shown in Figure 52, the multidepartment analysis conducted over four years revealed that implementing SM brought about dramatic changes for the manufacturer.

In Figure 51, the time difference between the traditional and SM framework is outlined. These timings were studied before and after implementing the SM framework. A change of 69% in timings for maintenance, HR, warehousing, accounts, production, sales and IT is shown. These values were obtained from the field study conducted on a mattress protector manufacturer.

In Figure 52, a cost–benefit analysis from 2018 to 2021 is discussed. As the bar graph shows, there were gradual improvements in interdepartmental performance after adopting the SM framework. This gradual improvement in interdepartmental performance led the overall performance of the manufacturing industry to reach an overall 95% improvement with just 5% in losses due to unavoidable scenarios. Further, interdepartmental performance was evaluated for communication improvements. A network traffic evaluation showed that the resources from various departments used an integrated ERP and MEs framework to communicate and allocate jobs. This integration resulted in reduced errors and improved decision-making capabilities.




| | Per day production | Number of employees | Production control flow | Tools and instrumentation | Maintenance scheduling | Quality processing |
|---|---|---|---|---|---|---|
| Time effectiveness | 4.6 | 136.8 | 7.6 | 20 | 20 | 7.6 |
| Time effectiveness | 7.6 | 167.2 | 11.4 | 20 | 20 | 15.2 |

Number of hours

Time effectiveness   Time effectiveness

**Figure 52 Cost–benefit analysis from smart manufacturing**

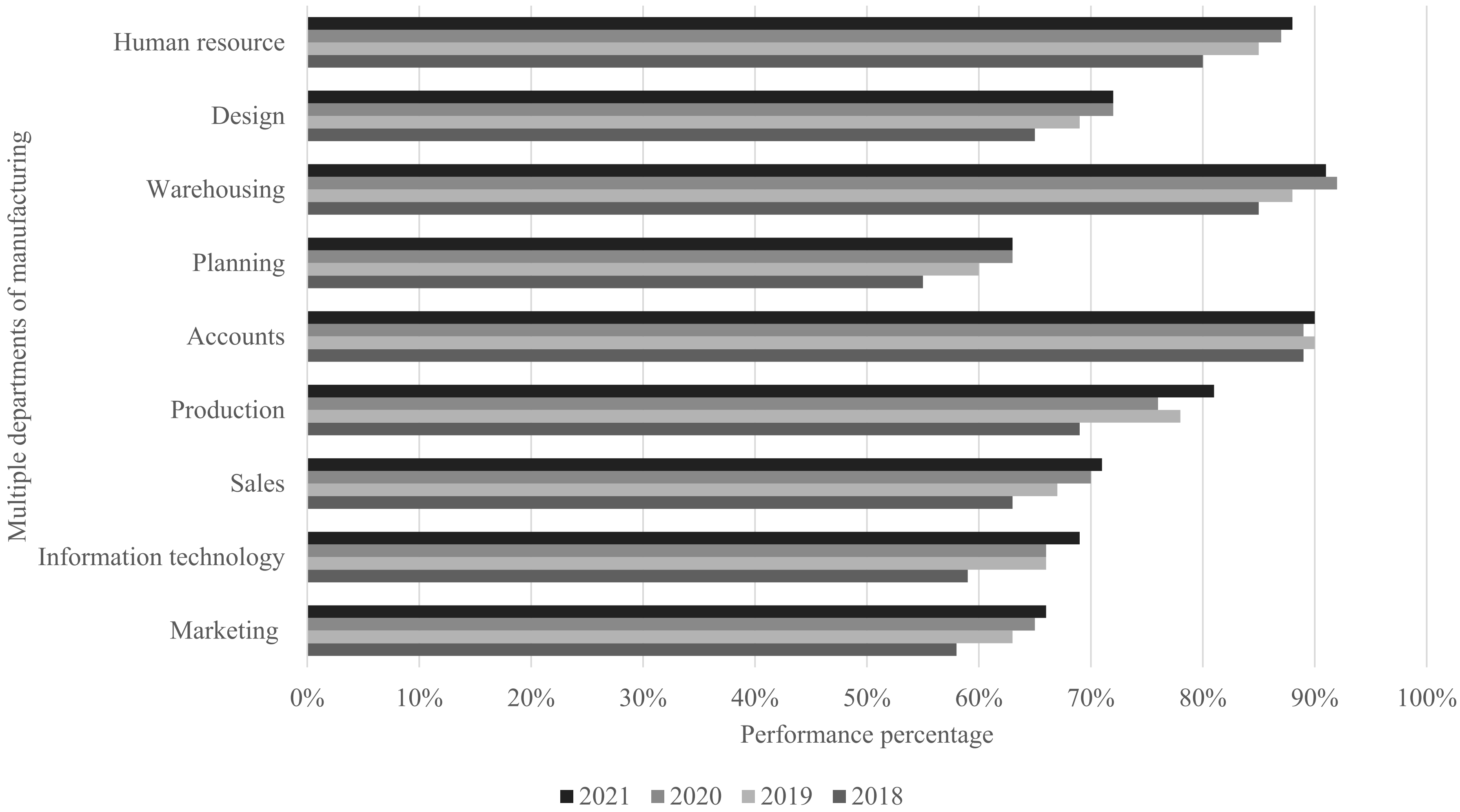



**Figure 53 Cost–benefit analysis multidisciplinary manufacturing industry**

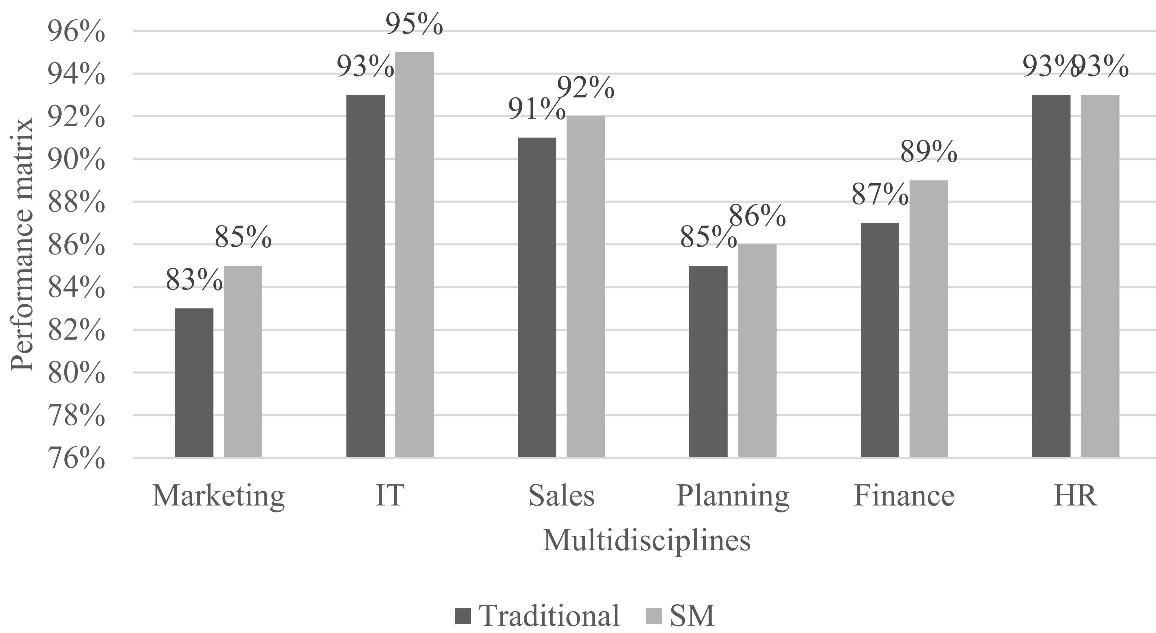



**Figure 54 Multidisciplinary decision performance analysis**

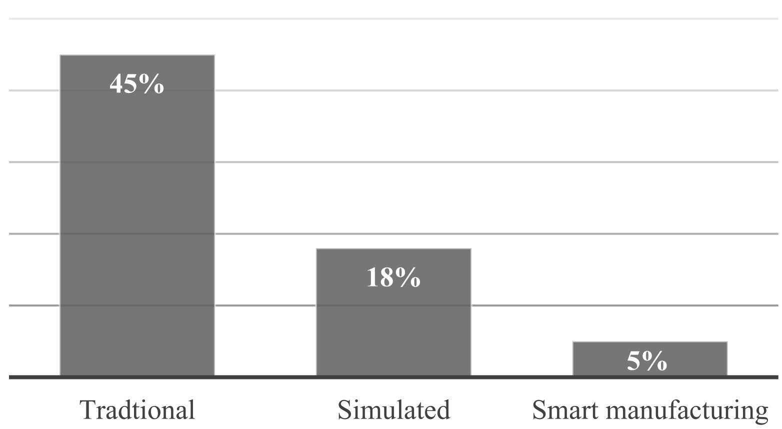



**Figure 55 Inefficiencies comparison in a decision-making framework with a cloud-integrated system**

## 6.7 Chapter Summary

This chapter presented a cloud-empowered SM and discussed the unique benefits for low-volume personalised products and enhancing decision-making frameworks. The following key points were discussed in this chapter:

i) Line balancing the whole manufacturing process was modelled in the AR/VR environment. The process involved the photogrammetric scanning of a shopfloor embedding geospatial data points for an environment. Further, the new balanced line involved augmenting machinery layout, human movement analysis and auxiliary robotic vehicles for improved flexibility. This manufacturing flexibility and the interpolation of various operations with a quick layout ability provided inclusivity for low-volume personalised product manufacturing.

ii) The CPS was developed by connecting VS, PS and DT in an integrated CC environment. Modelling various heterogenous operations, multidiscipline and relevant processes were challenges during the development of the cyber system. Characterising machine operations and interlinking CPS required RFID-based sensory outputs, which were developed using interconnected RFID datasets between various operations.

iii) The SM flow was designed to incorporate multiple operations of the textile industry. This integration started from receiving a work order in ERP system. Once the order was received, ERP communicated to the MES system. MES subdivided the work order into simple procedures with respect to individual operations. Once the order had been processed in MES, the operations were tacked using RFID tags. For example, the first operation (e.g., cutting the mattress protectors in required panels and integrating the sheets with RFID tags) and the next operations (e.g., sewing operations) were tracked throughout with RFID tags flowing through the automated manufacturing system (e.g., the Eton system). SM sensory data analytics provided continuous monitoring and helped suggest improvements to enhance efficiencies and improve decision-making. Once the operations were completed, the SM had personalised packaging, automated warehousing and dispatch capabilities.

iv) As manufacturing is multidisciplinary, CC enhanced the data analytical capabilities with dashboard decision tools. Integrating MES and ERP provided a synchronous flow with a cradle-to-cradle approach. The different departments, including suppliers and customers, were interconnected seamlessly with a real-time access capability. The SM system was compared with traditional manufacturing operations within various disciplines. The different disciplines and their related costs and times were compared (e.g., production, quality, material, control engineering, energy, tools and instrumentation, maintenance and employees). The results showed 18% cost benefits and 31% time reductions in SM compared with traditional manufacturing. The cost benefits and time reductions per day in multidisciplinary manufacturing were as follows: production—A$ 3,234.00 (32.34%) and 39.47 seconds (3%), quality—A$ 1,155.00 (11.55%) and 50 seconds (7.5%), material—no change and not applicable, control engineering—A$ 190.00 (1.90%) and 33.33 seconds (3.8%), energy—no change, tools and instrumentation—A$ 310.00 (3.10%) and not applicable, maintenance—A$ 256.00 (2.5%) and no change and employees—A$ 288.80 (2.89%) and 18.18 seconds (30.4%).

v) A cost–benefit analysis from the years 2018 to 2021 for the manufacturing multidiscipline was conducted for the decision-making framework. The results indicated that decision-making was enhanced after implementing the developed SM, which resulted in enhanced cost benefits. The decision-making framework was evaluated based on the communication protocols derived from the network traffic monitoring within various disciplines. Network traffic monitoring was embedded and harnessed via integrated ERP and MES communications within the SM framework (e.g., job allocation and resource planning). This minimised miscommunication and reduced ambiguity due to manual error. These were harnessed from the cloud-centric collaborative absolute decision-making framework. Implementing the developed SM enhanced the decision-making framework by 58% (2018) and 66% (2021) for marketing, 59% (2018) and 59% (2021) for information technology, 63% (2018) and 71% (2021) for sales, 69% (2018) and 81% (2021) for manufacturing, 89% (2018) and 90% (2021) for accounts, 55% (2018) and 63% (2021) for planning, 85% (2018) and 91% (2021) for warehousing, 65% (2018) and 72% (2021) for design and 80% (2018) and 88% (2021) for human resources.

vi) The entire SM framework was examined for decision-making inefficiencies within various operations and disciplines. Benchmarking studies were conducted to compare the traditional, simulated and developed SM. Inefficiencies within traditional and simulated manufacturing were 45% and 18%, respectively. The SM showed a 95% efficiency with less than 5% losses in decision-making processes. Thus, this research clearly established the efficacy of the developed SM framework for improving decision-making.

# 7 Conclusions and Recommendations

This chapter outlines the main research outcomes and offers recommendations to the manufacturing industry to enhance efficiency, focusing on decision-making frameworks and low-volume manufacturing.

## 7.1 Introduction

In this chapter, section 7.2 summarises the approach and outlines key conclusions of the research in terms of resolving key manufacturing challenges. Section 7.3 summarises the significant outcomes of the research and offers industrial recommendations. Positive feedback from the industry and industry recommendations are discussed in section 7.4.

## 7.2 Key Conclusions

The use of an SM framework allowed for the integrated cloud-centric transformative technologies of ML, CC and DT to be harnessed to enhance efficiency, decision-making frameworks and low-volume manufacturing. The framework led to efficiency gains using sensory technologies and ML-based intelligence to reduce machine idle and setup times and minimise failures by predicting unforeseen events. The ML algorithms with AD techniques could diagnose various sensory data, find faults and minimise downtime events, which would not be possible in traditional manufacturing. Intrinsic multidisciplinary bidirectional communication was established within the manufacturing by integrating ERP with MES. This enhanced communication protocols, material flows, inventory management, supplier and customer management and decision-making. The manufacturing system was controlled by automated overhanging conveyor systems linked to machines and related operations via RFID for balanced performance. This allowed for flexibility in low-volume personalised production, as well as rapid setups and changeovers and enhanced packaging. The major contributions of the research are as follows:

i) Chapter 1 detailed the research background, aims and objectives and novelty of the research, with an additional overview of the thesis organisation. The manufacturing industry is a major contributor to the GDP of a nation and, in 2019, accounted for 16% of worldwide GDP and over 14% of total employment across the globe. Per (ABS, 2019) data, manufacturing contributed 9% of the GDP of Australia, equating to A$ 100 billion, in 2019. This research aimed to develop an SM framework. The research problem discussed the current manufacturing paradigm the key challenges of inefficiency, the lack of decision frameworks and the need for agility in manufacturing to pivot to low-volume manufacturing. In total, 60% to 70% of the Australian manufacturing sector is made up of SMEs. Adoptions, affordability and the lack of a skilled workforce were major barriers to implementing SM frameworks. The novelty of this research lies in the integrated SM framework, which connects multiple disciplines, characterises heterogenous operations and minimises reworks and rejigging. This research outlined an integrated SM framework that enhanced communication and decision capabilities. Manufacturing agility allowed for the adoption of personalised low-volume manufacturing.

ii) A detailed literature review and manufacturing industry analysis were conducted to explore current gaps and challenges within the Australian manufacturing industry. SMEs often cannot afford to implement and upskill their workforce in terms of Industry 4.0 technologies (ABS, 2019). The disconnect between the multiple disciplines within manufacturing result in inefficiencies. These disciplines include production planning, administration, marketing and sales and resource management. Challenges must be addressed to transform manufacturing. An integrated manufacturing framework was required to enhance interdisciplinary connections and promote seamless operational connectivity. Major research gaps identified in the LR were the control of machine characters, which results in inefficiencies along with increased labour costs in Australia; the demand for inclusive personalisation due to global competitiveness; and ineffective communications between operators and operations, which results in waste. SM was implemented as singularity, providing the benefits of reducing costs and minimising manufacturing time (e.g., takt times, lead times, cycle times, operational costs, and administrative costs). AR/VR technologies were partially implemented in manufacturing targeting visualisation. However, an integrated framework of real-time visualisation along with physical machinery was found to be missing from the manufacturing paradigm. Research on heterogenous operational data acquisition and related data analytics for enhanced efficiency was also lacking missing (e.g., using ML algorithms found in singularities).

iii) A case study on the manufacturing industry was conducted on a manufacturer in the textile industry that had complex and heterogenous operations that were multidisciplinary, inefficient, disconnected and required large variants with low-volume manufacturing. The results of the field study showed that absorbent time was required for various products using traditional manufacturing (e.g., a single mattress protector took 158 seconds to produce, a queen mattress protector took 165 seconds, and a super king mattress protector took 180 seconds). The manufacturer used many intricate operations, such as cutting, laying, sewing, folding and packing. These operations were integrated on a single platform using the developed SM framework, and the same technology shows potential to be implemented in other similar manufacturing companies.

iv) The operations of the textile manufacturer were heterogenous with several disconnects. Further, the operational takt times varied, meaning lines were imbalanced. In addition, the large variations in product ranges required the manufacturing systems to be agile. A field study was conducted to benchmark current practices and pinpoint key challenges. Several efficiencies gains were documented from the traditional to simulated environment in the field study: the cutting operation improved from 55% to 89%, transferring was enhanced from 58% to 85%, sewing from 56% to 88% and packing from 59% to 90%. Thus, the simulated system resulted in overall efficiency gains of ~31% compared with traditional practices.

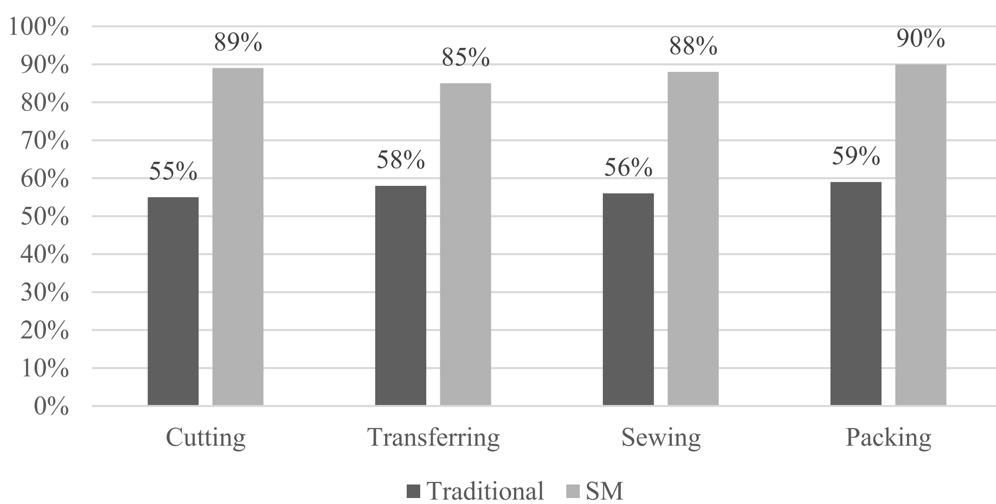



**Figure 56 Field study comparison of traditional and smart manufacturing**

v) The SM framework was introduced to address manufacturing challenges and the previously identified limitations. The main challenges identified through the LR, and field studies were inefficiencies due to unplanned machine breakdowns, idle/ setup times due to lack of integrated framework, a lack of communication and decision-making capabilities, rework and rejigging, technology adoption and upskilling issues, affordance and implementation, disintegrated disciplines and the lack of manufacturing agility for low-volume manufacturing. The SM framework integrated VS and PS within the integrated cloud-centric DT platform. This data integration and analytics provided seamless communications within various disciplines. This ensured enhanced decision-making and seamless manufacturing in packaging and beyond. The SM framework combined various transformative technologies (e.g., ML, CC, CNR and AR/VR) in an integrated solution to capture heterogenous operational characteristics. Further, AR/VR technologies were used to visualise operational sequencing and for takt time analysis and optimisation for enhanced efficiencies through simulations. In addition, ML algorithms were used to analyse machine characteristics and behaviours, as well as for automated prediction strategies. Storage, access control and behavioural predictions from the centralised cloud-centric platform enhanced data analytics capabilities. Raspberry Pi was used to establish the data acquisition and analysis for enhanced efficiency.

vi) The SM framework used ML-based intelligence to enhance efficiencies and the decision-making framework. AD techniques were used by incorporating ML over sensory data. Sensory data were obtained from various operations using different sensors embedded in the machines. These data sets were complex and inherited multiple dimensions. Hence, monitoring and controlling these HD datasets was inherently complex. The ML algorithms were distinct and posed potential capabilities to address the aforementioned HD datasets generated from the manufacturing operational sensors. Among the proposed ML algorithms, IF, random forest, KNN, SVM, MLR, and decision trees were trialled for performance testing to detect and normalise anomalies in the HD datasets.

vii) Of the various algorithms for AD techniques, IF and KNN were the best fit algorithms for the HD data, with an AD score of nearly 96%, which was the highest of all the algorithms. A case study was conducted on a textile manufacturer on a sewing operation. Ten sensors were tested and gave the following readings: 2.440, 47.309, 52.127, 44.531, 77.184, 13.093, 16.168, 52.910, 15.119 and 39.726. Based on machine failures, Sensor_08 threshold was identified as between 14.98 and 15.98. Hence, the IF algorithm identified and predicted the failure as Sensor_08 for AD. In conclusion, implementing the ML and AD algorithms on the manufacturing data resulted in an overall ~30% increase in efficiency. The cutting, sewing, folding and packing measures resulted in a 30%, 29%, 26% and 26% increase in efficiency, respectively.

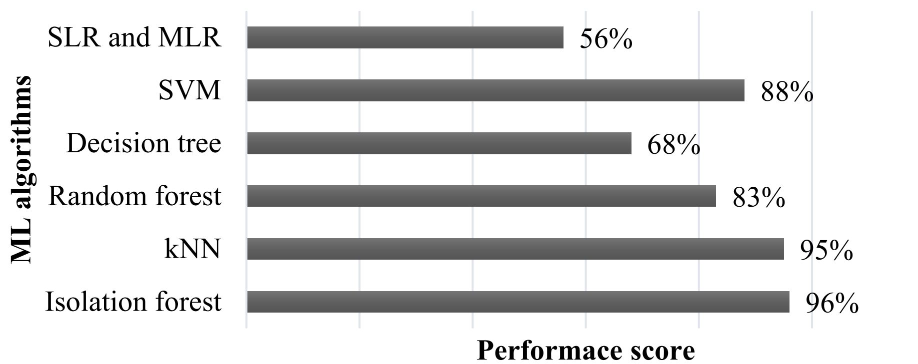



**Figure 57 Algorithm performance matrix**

viii) Efficiency gains in manufacturing were addressed in Chapter 5 by implementing ML through the SM framework. Chapter 6 addressed low-volume manufacturing and decision-making frameworks. CPS was developed for the textile industry to validate the SM framework. Further, several analyses were conducted by benchmarking SM compared with traditional manufacturing, and the results indicated an 18% cost benefit and 31% time reduction. The cost benefits and time reductions per day in multidisciplinary manufacturing were as follows: production—A$ 3,234 (32.34%) and 39.47 seconds (3%), quality—A$ 1,155 (11.55%) and 50 seconds (7.5%), material—no change and not applicable, control engineering—A$ 190 (1.90%) and 33.33 seconds (3.8%), energy—no change, tools and instrumentation—A$ 310.00 (3.10%) and not applicable, maintenance—A$

256.00 (2.5%) and no change and employees—A$ 288.80 (2.89%) and 18.18 seconds (30.4%). An interdepartmental performance analysis was conducted annually. From 2018 to 2021, there were substantial improvements within the different manufacturing departments: marketing (8%), IT (10%), sales (8%), manufacturing (12%), accounts (1%), planning (8%), warehousing (6%), design (7%) and HR (8%). Inefficiency within traditional and simulated manufacturing was 45% and 18%, respectively. The SM proposed in this research showed a 95% efficiency with less than 5% losses. Thus, the efficacy of the developed SM framework was clearly established.

## 7.3 Important Outcomes and Recommendations

This section covers the important outcomes and recommendations made for the manufacturing industry, as follows:

i) The problems faced by SMEs were identified, and countermeasures were recommended. An integrated SM system was developed to address inefficiencies, decision-making and low-volume manufacturing. This system must be normalised in Australian SMEs.

ii) Three important manufacturing problems were discussed. The first concerned efficiency. The results of the research showed that implementing ML algorithms in the manufacturing industry can provide a solution to important challenges. The methodology used in this research is recommended for all Australian manufacturing SMEs. Implementing ML algorithms will promote change within traditional manufacturing methods in Australia, which will boost GDP.

iii) Two appropriate algorithms were recommended. The accuracy of KNN and IF was demonstrated on the complex data generated. The major advantages of these algorithms were sub-sampling, swamping and masking. Hence, these algorithms are recommended for analysing manufacturing data.

iv) Of the various cloud-deployment techniques and implementation strategies, the use of hybrid cloud storage was recommended. Hybrid cloud storage has an edge over the other cloud-deployment methods of private, public and community deployment.

Hybrid cloud storage mainly uses private and public deployment strategies. This combination of technologies resolved the intrinsic job of the anywhere, anytime strategy.

v) The research showed that the manufacturing industry is in need of comprehensive and informative decision-making frameworks. Implementing such a framework in the manufacturing industry led to an analysis of interdepartmental performance. This analysis pinpointed the major challenges and solutions affecting manufacturing and identified critical decisions that must be taken.

vi) AWS as a cloud server was used to validate the framework for the advanced implementation of cloud-based real-time event failure detection. This operated uninterrupted in the manufacturing scenario.

vii) Online instants of Anaconda version (Jupyter lab or Jupyter notebook) are strongly recommended for workspaces in which ML is implemented. Further, modelling software, such as 3Ds Max, Solidworks and Bender, is recommended for modelling applications in CPS. 3D simulators, such as virtual components, can be used for real-time simulation.

## 7.4 Endorsements

The research has been accepted and endorsed by industry partners and journals and has received positive feedback from industry experts, who have made recommended for similar industries. Industry experts, such as the Innovative Manufacturing Cooperative Research Centre (IMCRC), reviewed the research, which was validated on a mattress protector manufacturing company. The researcher also received recognition through public appearances and guest lectures, as well as in renowned publications.

This research outcomes were discussed in guest lectures at Swinburne University of Technology and the Indian Institute of Technology, Hyderabad, India. The case study and the implementation strategies were discussed to explain the industry standards of SM implementation to students.

## 7.4.1 Industry Partner Acceptance

The research was conducted over a period of three years in relation to an Australian mattress protector manufacturer in association with IMCRC. Progress was reviewed regularly by industry partners Sleepcorp Pty. Ltd. and IMCRC. Board meeting were held monthly, and quarterly reports were submitted. Below are the dates and details of quarterly reports and milestones achieved.

### 7.4.1.1 Quarterly reports

i) Sleepcorp, IMCRC innovative project – April 2019
ii) Sleepcorp, IMCRC innovative project – July 2019
iii) Sleepcorp, IMCRC innovative project – October 2019
iv) Sleepcorp, IMCRC innovative project – January 2020
v) Sleepcorp, IMCRC innovative project – April 2020
vi) Sleepcorp, IMCRC innovative project – July 2020
vii) Sleepcorp, IMCRC innovative project – October 2020
viii) Sleepcorp, IMCRC innovative project – January 2021
ix) Sleepcorp, IMCRC innovative project – April 2021
x) Sleepcorp, IMCRC innovative project – July 2021
xi) Sleepcorp, IMCRC innovative project – October 202

## 7.5 Milestones Reached

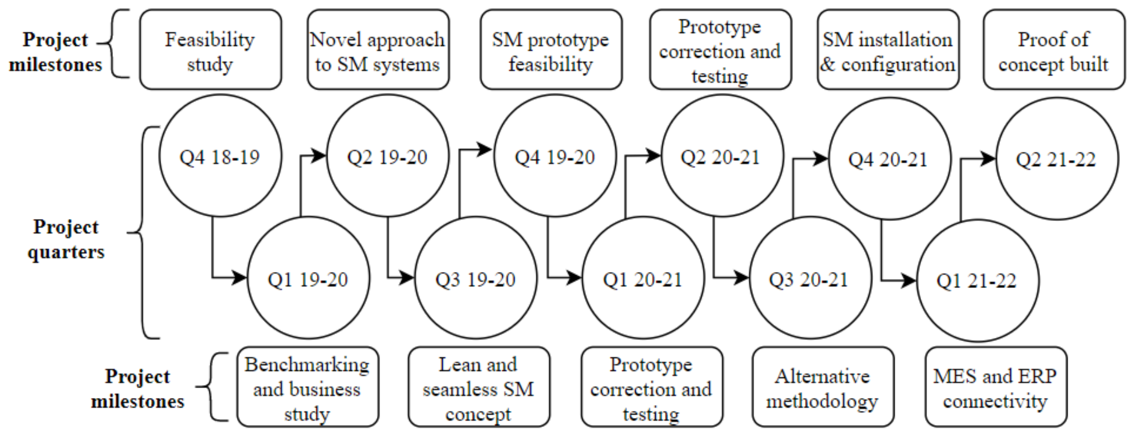



**Figure 58 Project milestones**

There were major milestones for the eleven quarters of the research project conducted on a textile industry manufacturer. In the first quarter, a feasibility study of the textile industry was conducted. In the next quarter, current standards of manufacturing technologies were benchmarked, and a business case study was designed. Following the novel approach of an SM framework, the advanced technologies ML, CC, CPS and DT were considered. A seamless and lean-manufacturing framework was discussed by weighing the capabilities of SM. Prototype testing was conducted for two quarters in the 2020–2021 financial year. Depending on the observations from the prototype, an alternative or modified methodology was introduced. This novel SM framework was configured for textile manufacturing. Lastly, MES and ERP were integrated, and a proof of concept was demonstrated based on a real-world case study.

## 7.6 Publications

i) **Sourabh Dani**, Jiong Jin and Ambarish Kulkarni, ‘Current state of art industry survey in Industry 4.0 manufacturing industries’, Journal of Industrial Engineering and Management (under review).

ii) **Sourabh Dani**, AK Rahman, Jiong Jin, and Ambarish Kulkarni, ‘Real-time Cloud Empowered VMS’, published for the special edition of ‘Handbook of Real-time Computing’ for Springer edition.

iii) **Sourabh Dani**, Jiong Jin and Ambarish Kulkarni, 'Comprehensive survey of Real-time anomaly detection in High Dimensional Data in Manufacturing scenario', submitted to the IEEE International Conference on Cloud Computing (under review).

iv) **Sourabh Dani**, Jiong Jin and Ambarish Kulkarni, 'Real-Time Anomaly Detection in Smart Manufacturing System' conference on Industrial Connectivity for a manufacturing process using Cyber-Physical Systems (under review).

v) **Sourabh Dani**, AK Rahman, Paul Shuva, Jiong Jin, and Ambarish Kulkarni, 'Cloud Empowered High Dimensional Anomaly Detection', submitted to the internarial journal of IEEE (impact factor: 3.367).

# 8 Future Scope

This chapter discusses the future scope this research and outlines the direction of future developments and improvements to ML, CC and CPS in SM frameworks.

## 8.1 Introduction

This research has many future applications that are not limited to manufacturing. Similar frameworks could be implemented in the construction, mining and transport industries. However, before exploring the multitude of possibilities of this research in different industries, manufacturing scenarios should be explored in further detail.

## 8.2 Effective Modelling of Self-learning Algorithms

Common manufacturing problems were addressed by implementing self-learning algorithms. These algorithms must be developed and modified for high-scalable environments and should be robust and reliable. This research paves the way for reduced event failures; however, the development of algorithms was not explored in detail. When implementing algorithms on manufacturing data, many inbuilt problems were encountered, such as ML model latency, inaccuracy and non-environment friendly. Further, the algorithms researched were modified for the case study. This modification of cross-platform performance should be studied in more detail. Rapid developments in the field of manufacturing demand high accuracy and reliable models. Although all possible supervised and unsupervised algorithms were explored in this research, future research should focus on big data developments.

ML has become powerful in the last decade, and the intelligence that algorithms create is intelligent. Intelligence is a must-have feature for SM systems. The interdisciplinary actions of ML reveal its capabilities in the fields of mining, transportation, industrial automation and others.

## 8.3 Cyber Security for Seamless Manufacturing

For all of the advantages that SM may provide, it also necessitates a more complete security strategy. The catalysts for SM are seamless connection and smart gadgets, but they may also be a conduit for security concerns. The increasing usage of publicly accessible technology in industrial control systems, as well as the creation of increasingly connected, information-enabled organisations, raises security threats, as well as the obligations of both control system suppliers and users. Industrial control systems have traditionally relied on proprietary technology and have been kept separate from information systems in most businesses. The systems were mostly incompatible, and the commercial technologies employed in office environments simply did not match the control system's needs. Commercial technologies have been adopted for use in control systems as they have improved in recent decades, resulting in lower prices, more compatibility, and greater simplicity of use. Connectivity between systems has grown easier and more anticipated as a result of these advancements.

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