DEVELOPING A PROTOCOL FOR COLLABORATIVE DECISION-MAKING IN A SMART MANUFACTURING ENVIRONMENT

JEANNE COETZER

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Promotor: Prof. HJ Vermaak (PhD: Electrical Engineering)
Co-promotor: Dr. RB Kuriakose (D Eng.: Electrical Engineering)
Co-promotor: Dr. G Nel (PhD: Computer Information Systems)

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2023

DECLARATION OF INDEPENDENT WORK

DECLARATION WITH REGARD TO INDEPENDENT WORK

I, JEANNE COETZER, identity number ________ and student number _______, hereby declare that this thesis submitted to the Central University of Technology, Free State for the degree DOCTOR OF PHILOSOPHY in INFORMATION TECHNOLOGY, is my own independent work; and complies with the Code of Academic Integrity, as well as other relevant policies, procedures, rules and regulations of the Central University of Technology, Free State. In addition, it has not been submitted before to any institution by myself of any other person in fulfilment (or partial fulfilment) of the requirements for the attainment of any qualification.

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ABSTRACT

The Fourth Industrial Revolution places different rapidly advancing technologies like the Internet of Things (IoT), Internet of Services (IoS), Internet of Everything (IoE) and Cyber Physical Systems (CPS) at the centre of developing autonomous manufacturing systems. The development of these systems within the environment of Industry 4.0 expects significant changes in tasks and demands on the human in the manufacturing process and recognises that humans and machines are homogeneous parts of a larger diverse body consisting of collaborative and autonomous components.

According to the Industry 4.0 concepts, all objects in the manufacturing world have assimilated processing and communication capabilities which highly affect machine-to-machine communication. However, a considerable consequence is that of the effect it will have on human-to-machine interaction. It is occasional that automated systems are solely autonomous; a level of human interaction is usually present although this challenge is not always considered. In mixed environments, automated systems and humans need to collaborate for the completion of a process. Currently, there exists very little research on how a collaborative decision-making process can be developed such that the worker's acceptance and adaptation to the process is taken into cognizance.

This research identifies the lack of collaborative decision-making processes as a research gap and introduces the problem with an extensive literature review that focuses on the research done in this field, followed by a review of potential models for human technology interaction. A case study of an automated water bottling plant to advance the study in collaborative decision-making is introduced for the execution of several experiments to compare a fully automated approach versus a collaboration between the human operator and the system.
A single group experimental approach is used to prove the theory while also identifying where the human will best fit into the automated procedure resulting in an optimized production process. The hypothesis is that the completion time for customer orders will be optimal when the human and the machine collaborate for the completion of the production process.

DEDICATION

To my two sons, Edwin and Stefan Coetzer for their encouragement, support and prayers throughout during this journey.

To my later mother, Stephanie Markram, who always believed in me and encouraged me to reach for the stars. Thank you, Mom, you would have been so proud!

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List of Abbreviations

AR	Augmented Reality
CPPS	Cyber-Physical Production Systems
CPS	Cyber Physical Systems
HCI	Human-Computer Interaction/Interface
HMI	Human-Machine Interaction/Interface
HTI	Human-Technology Interaction
ICT	Information and Communication Technologies
IoE	Internet of Everything
IoS	Internet of Services
IoT	Internet of Things
NHMI	Natural Human-Machine Interface
OEE	Overall Equipment Effectiveness
NIST	National Institute of Standards and Technology
PLC	Programmable Logical Controllers
SAS	Statistical Analysis System
SCADA	Supervisory Control and Data Acquisition system
SMU	Smart Manufacturing Unit
TTM	Total Time to Manufacture
VR	Virtual Reality

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CHAPTER 1: Introduction to the study environment

1.1 Background Information

The Fourth Industrial Revolution places different rapidly advancing technologies like the Internet of Things (IoT), Internet of Services (IoS), Internet of Everything (IoE) and Cyber Physical Systems (CPS) at the centre of developing autonomous manufacturing systems [1]. The development of these systems within the environment of Industry 4.0 demands significant changes in tasks undertaken by humans in the manufacturing process and recognises that humans and machines are homogeneous parts of a larger diverse body consisting of collaborative and autonomous components [2].

According to the Industry 4.0 concepts, all objects in the manufacturing world have assimilated processing and communication capabilities, which highly affect machine-to-machine communication [2]. However, a considerable consequence is the effect it will have on human-to-machine interaction. Although Industry 4.0 focusses mainly on the linking of machines and digital systems [3], the human operator retains skillsets that automated machines cannot match and, as such, the integration and collaboration of humans with technology and systems is an emerging field of Industry 4.0 research [3]. Humans possess skills such as their unique capability for problem-solving and decision-making, dexterity and sensory skills that is not present in a machine or automated system [3]. Automated systems are solely autonomous, and as mentioned, a level of human interaction is usually present although the challenge of including humans in the autonomous systems are not always considered. In mixed environments, automated systems and humans need to collaborate for the completion of a process. Currently, there exists very little research on how a collaborative decision-making process can be developed such that the worker's acceptance and adaptation to the process is taken into cognizance.

This research identifies the lack of collaborative decision-making processes as a research gap and introduces the problem with an extensive literature review that focusses on the research done in this field, followed by a review of potential models for human technology interaction. A case study of an automated water bottling plant to advance the study in collaborative decision-making is introduced for the execution of several experiments to evaluate a fully automated approach versus a collaboration between the human operator and the system.

A single group experimental approach will be used to prove the theory that collaborative decision-making between the human and machine will lead to optimal production time of an automated system in a Smart manufacturing environment. Analysing and validating the collected data, using the single group experiment, will be realized by implementing a software namely Statistical Analysis System (SAS), which is a programming language used for statistical analysis affording results that is able to accurately predict the process times of the automated approach versus the collaborative approach.

The single group experiment also aims to identify where the human will best fit into the automated procedure resulting in an optimized production process. The hypothesis is that the completion time for customer orders will be optimal when the human and the machine collaborate for the completion of the production process in the automated system.

1.2 Problem Statement

The successful operation of an automated system is highly dependent on Human-Technology Interaction (HTI) as well as efficient collaboration between the workforce and the automated system. The absence of collaborative decision-making processes is identified as a challenge that results in a greater Total Time to Manufacture (TTM) a product, hence affecting the optimum performance of automated systems and thus seen as a research gap.
This problem is elevated within the Industry 4.0 environment that include not only automated systems but also integrated HTI and Internet of Everything (IoE) technologies.

1.3 Research Hypothesis and Objectives

1.3.1 Hypothesis

Collaborative decision-making will assist in reducing the TTM, hence it will have a positive impact on optimizing the production process within a Smart manufacturing plant.

1.3.2 Research Aim

The aim of this research is to investigate and establish the importance of human intervention in a collaborative decision-making process for the optimum completion of tasks performed by an Information and Communication Technologies (ICT) enabled Smart automated manufacturing system and propose a protocol to determine the tasks/actions best performed by machine, by a human and a collaboration of human and machine.

1.3.3 Research Objectives

- Testing, analysing and validation of the production time for a machine only and the collaboration of a human and machine system.
- Determine the effects of human-machine collaboration on an automated production system from the testing process.
- Developing of a protocol with guidelines on tasks/actions best performed by a machine, by a human and a collaboration of human and machine.

1.4 Research Methodology

The fact that collaborative decision-making is lacking in modern Smart factories has been identified as a problem [4] and subsequently, the research that is being conducted aims to provide a solution to assist in solving the challenge. The aim of this research is to investigate and establish the importance of human intervention in a collaborative decision-making process for the optimum completion of tasks performed by an ICT enabled Smart automated manufacturing system.

In order to meet this challenge, the study will involve the development of a case specific application for the Human-Machine Interface (HMI) to enable collaborative decision-making between the machine and the human operator. This will be done by using an existing, fully automated water bottling plant in a Smart manufacturing environment as a case study.

The water bottling plant is split into three sections which is run using three Smart Manufacturing Units (SMU's). The first SMU is tasked with filling water bottles in 330ml and/or 500ml bottles, the second SMU caps the filled water bottles while the third SMU packs the completed orders.

In achieving the specified objectives, a single case experimental study will be executed. A single test case will be employed to prove the theory, which is that the completion time for orders received, will be optimal when the human and the machine collaborate for the completion of the production process. For this purpose, two different scenarios will be used to determine the impact of collaborative decision-making in the automated system namely the machine only and secondly a collaboration between the machine and the human operator.

The scenario of machine only will be the control case, as the system will complete the production process without any human intervention, whereas the human-machine collaboration will be used as the test case.

The testing of the water bottling plant is intended to be executed in real-time for determining the average time for filling one bottle using the automated approach and the same test will be run whereby the human will be introduced into the control loop to determine the average time for filling a bottle with introducing human intervention. Several scenarios are going to be presented for the collection of data during the execution of the experiments. Analysing and validating of the data gathered will be attained by implementing a software, called Statistical Analysis System (SAS), which can accurately predict the process times of the automated approach as opposed to the collaborative approach.

The single-case experiment will be used to compare the two scenarios by utilizing the outputs from the SAS program to prove that collaborative decision-making contributes to optimum production in a Smart automated environment.

In conclusion, the research aims to develop a protocol with some guidelines on tasks/actions best performed by a machine and tasks/actions best performed by a collaboration between the human operator and the automated system.

1.5 Layout of the Thesis

Chapter 1: Chapter 1 serves as an introduction, providing background information, current operation of manufacturing plants and expounding the intended contributions and merit of the study using an appropriate research methodology.

Chapter 2: The most relevant contributions of the content that was reviewed were discussed in Chapter 2 through a review of literature relating to the study. This chapter initially gives an overview of Industry 4.0 and identifies the fast advancing technologies which is set to modernize the way manufacturing has been done up to now. Smart manufacturing and the role it plays in Industry 4.0 is highlighted, followed by a discussion of Human-Computer Interaction, Human-Machine Interaction and Human-Technology Interaction, which are three terms related to the interaction with the rapidly developing technologies of the Industry 4.0 era. Collaborative decision-making is defined and discussed as this is where the research gap was identified – a lack of collaboration between humans and machines in the Industry 4.0 environment. Potential models of Human-Technology Interaction are discussed namely a machine only approach and a combination between the human and machine. Finally, the limitations of existing research are emphasised.

Chapter 3: The aim of Chapter 3 is to focus on the research methodology employed by the researcher and provide an overview of the methodology for the study. The steps for developing a generic protocol is provided as this is the main aim of this research study. A detailed description of the case study selected for the study is provided as well as how the chosen experimental data collection methods were used whilst conducting the research.

For purposes of determining the effectiveness of the automated machine, the Overall Equipment Effectiveness (OEE) is discussed as the OEE score determines where the best fit for the human will be in the production process. SAS is introduced as the software application for programming the code with the intention to provide accurate results on the experiments conducted for the case study.

Chapter 4: The aim of this chapter is to showcase the results obtained from the experiments conducted. The chapter shares the results for each scenario that was tested in fully automated mode and secondly the experimental setup and results of the human-machine collaborative approach will be revealed. An analysis of the two sets of results will be compared to determine which process contributes to the optimization of the production process and where the best fit will be for the human to intervene in an automated production process. Outputs generated by SAS are going to be used to analyze and compare the results.

Chapter 5: The aim of this chapter is to summarize the limitations of existing research followed by a review of the results for each scenario that was tested during the execution of the experiments. Insights gained from the analysed data will be shared and based on the results, the research aims to show how some of these limitations were overcome.

Chapter 6: This chapter looks back at the work done in the project and brings to the fore goals achieved during the project in terms of adding knowledge to the specific field of research, research contributions and the future scope of work.

CHAPTER 2: Literature Review

2.1 Introduction

The aim of this chapter is to look at the literature review that was undertaken preceding and during this study. The literature review was explored to support the direction of the study while assisting in establishing the research gap and familiarizing the researcher with current and former research relevant to the objectives of this study.

2.2 Industry 4.0

Since the dawn of the Industrial Revolution dramatic increases in industrial productivity have been driven by technological advances throughout the different revolutions as portrayed in Figure 2.1 [5]. The term 'Industry 4.0' refers to the Fourth Industrial Revolution which is the popular term to describe the current changes of the industry landscape [2], specifically in the production and manufacturing environments [6].

Preceding Industry 4.0 were three other Industrial Revolutions: the First Industrial Revolution occurred between the late 1700's and early 1800's with the invention of the steam engine which introduced itself with the use of water or steam power using coal as energy source for new mechanical production facilities [7], [6].

The Second Industrial Revolution began in the 1870's with the invention of the internal combustion engine which led to the use of oil and electricity to power mass production in very fast growing industrial developments [7].

The introduction of the digital era came with the Third Industrial Revolution which started in the 1960's and was characterized by the automation of production with the use of electronics and information technology [7],[2].

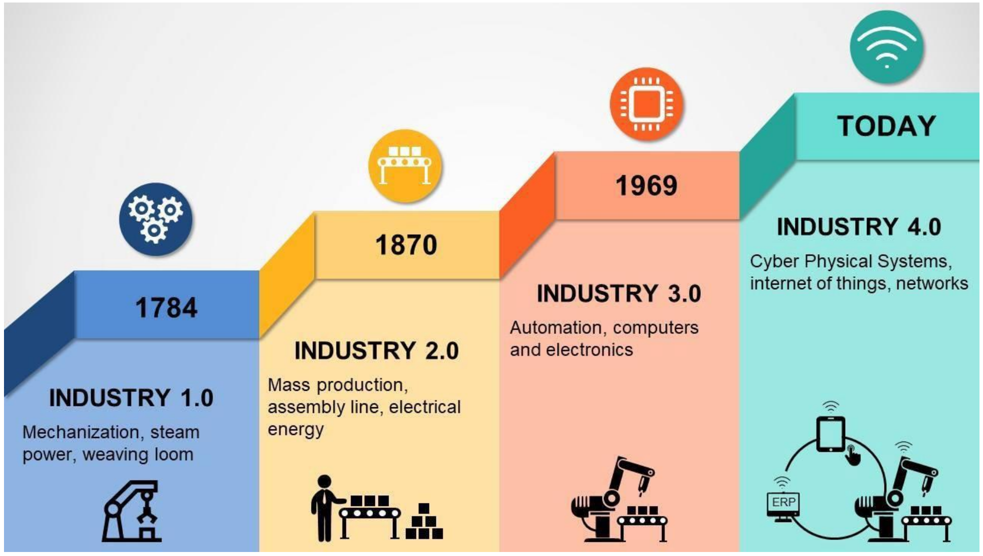

Figure 2.1 The evolution of the Industrial Revolutions [7].

The Fourth Industrial Revolution is a new concept of manufacturing and is concerned with the analysis and use of information and communication technologies to notify and enhance all the processes associated with the manufacturing sector and connecting manufacturing processes from design up to the end of the product lifecycle [8].

The digital technology from recent decades are engaged to a whole new level with fast advancing technologies in Industry 4.0 such as the Internet of Things (IoT), Internet of Everything (IoE), virtual reality (VR), augmented reality (AR), access to real-time data and the introduction of Cyber Physical Systems (CPS) with the help of interconnectivity between technologies [9], [10].

Industry 4.0 involves industrial automation and integration of new production technologies for the enhancement of work environments while increasing quality and productivity [1]. Industry 4.0 builds on the advances of the Third Industrial Revolution as production systems already have existing computer technology which is now extended by network connections allowing communication with other systems and facilities in an automated manufacturing environment [2].

Industry 4.0 is set to modernize the way manufacturing has been done up to now [11]. By utilizing the abovementioned technologies, production diversity can be implemented and factories can employ a make-to-order approach as assembly lines for Smart manufacturing in the Fourth Industrial Revolution environment are designed to adapt and meet the demand for producing a variety of products as per customer orders [12],[13].

Industry 4.0 is geared towards progressively more individualised customer needs [14] where most industries now choose the make-to-order approach as opposed to the make-to-stock approach, which was the traditional approach employed by industries [12]. In the make-to-stock approach raw materials are stocked up ahead of customer demand, production and shipping while the variety of products produced are restricted [12]. A problem that arises from the make-to-stock approach is that the demand for products are stochastic [15] which means that it cannot be predicted precisely what the demand will be and the factory has to depend on a random probability for manufacturing of their products. By implementing the make-to-order business strategy, customers are able to request and order products based on their specific make-to-order specifications [11]. Exploiting this strategy, several problems are overcome such as minimizing unsold or unutilized stock, improved product variation and decreasing of financial risk to the manufacturer [12].

This strategy centres around the progressions made into the research in technologies mentioned previously such as IoT's, CPS and 5G technologies, which uses high speeds of data transfer. As such, Industry 4.0 technologies lead to automated production systems and subsequently Smart manufacturing in which people, machines, components and production systems communicate via a network for automated and collaborative production processes [9].

2.2.1 Smart Manufacturing

Smart manufacturing is a term which is widely used to describe the current and future trends in manufacturing and lies at the centre of the Industry 4.0 environment [9]. Smart manufacturing can be described, according to the National Institute of Standards and Technology (NIST) as fully assimilated, collaborative manufacturing systems that meet certain conditions and requirements in the factory responding in real-time, not only in the supply network but also in customer requirements.

Smart manufacturing integrates production and manufacturing resources with computing platforms, sensor technology, control, simulation, communication technology, data control and measurement as well as prognostic engineering [16] resulting in substantial consequences within the manufacturing environment. According to Kumar, et.al [10], [17] with Cyber-Physical Production Systems (CPPSs) in Smart factories, it is anticipated that human operators will be more involved in intellectual work and less physical work. Studies done by Sparrow, et. al [3] and Pacaux-Lemoine et. al [18], have stressed that human awareness is necessary in modern manufacturing systems, while keeping human decision-making in the loop at different automation levels.

As such, a significant effect of Industry 4.0 and Smart manufacturing is the change it brings forth in the workplace organization and job satisfaction among the workforce [2]. In respect of these changes a result is that the role of human operators in Smart manufacturing will be moved into activities of decision-making, interpreting information and observing real-time sensor data [10]. With the integrated processing and communication abilities of the above mentioned technologies, an important subject is that of the effect that it will have on human-machine interaction [19]. Another important concern, which is not always considered, is the level of human interaction which is continuously present in automated systems and therefore should be taken into consideration as to how to incorporate human skillsets in the Industry 4.0 environment in order for the human to become part of the production control loop [20], [21].

The success of automated systems are highly dependent on the interaction between humans and machines as well as collaborative decision-making in the process [4]. Humans have a natural level of intelligence with unique, critical skillsets that can be beneficial to self-adjusting, preventive and corrective actions [2] that can be employed in manufacturing systems for supervisory control, decision-making and corrective or adaptive actions which leads to improved levels of system performance [22].

As Industry 4.0 evolves, so does the way people interact with technology and this leads to more sophisticated interfaces for communicating and interacting with technology [1] while also considering how the human element must be integrated in the Industry 4.0 environment [2].

With the rise of the digital era over the last few decades, bringing with it the development of technologies such as mobile devices, robotics, artificial intelligence, the Internet, sensors and Internet of Things (IoT's), a paradigm shift was brought on to Human-Computer Interaction (HCI). Sensors allow for new possibilities of interacting with technology [23]. As the context of work and sub-tasks in the production process has significantly started to change within the environment of Industry 4.0 and Smart manufacturing, the concept of HMI's changed considerably [10]. With the introduction of mobile devices, the way people interact with technology has changed extensively - the use of touch and gesture-based interaction has become the norm.[4].

However, these recent advances in computing architecture, machine learning and sensor technology will have a much wider impact on how people interact with machines. Three terms that are used in the field of computer science to refer to the interaction between humans and machines are Human-Computer Interaction (HCI), Human-Machine Interaction (HMI) and Human-Technology Interaction (HTI).

It is noteworthy to discuss these three terms related to the interaction with technology due to the nature of the rapid development in the Industry 4.0 era and the impact it has on collaboration between humans and machines as well as on the field of Information and Communication Technologies.

2.2.2 Human-Computer Interaction (HCI)

Since the 1960's, the rapid advances of information systems and accompanying technologies led to the extensive development of research on human-computer interaction [24]. The goal of HCI is to connect people to communication systems and computers in a manner that are both useful and accessible in an efficient and effective way [25].

HCI is a multidisciplinary area of study that focusses on the design of computer technology and the interaction between humans and computers which includes cognitive science, computer science, robotics [26], graphic design, psychology, information and communication technology, sociology and human-factors engineering as it intends to simplify the execution of computer and communication system tasks [25].

HCI refers to the study of the ways in which technology influences human work and activities [27]. Another definition is, that "HCI is the process of communication between users and computers (or interactive technologies in general)" [28]. The term "interactive", in this context, refers to the creation of interactive technologies that support people in executing everyday tasks [29].
Interaction with these technologies takes place through a Human-Computer Interface which can be defined as the communication between a human and a computer system by using input and output devices to enable a user to use a computer system in an efficient, effective and satisfactory manner [30], [31].

Previous research has indicated that computer manufacturers and software designers have identified the benefits of creating usable products and argue that creating usable interfaces may have a huge impact on the interaction, usability and effective use of applications and devices [32]. Product design should consequently be supported by the user experience to allow for the adaptation and acceptance of technology by the workforce in the Industry 4.0 era. The user experience (UX) refers to the expectation of users of having systems or applications to not only function well, but to be fun, satisfactory, efficient and enjoyable to use [4].

2.2.3 Human-Machine Interaction (HMI)

Since the beginning of the development and design of interactive technologies, almost every thinkable work environment; from office work, health care, computer design and engineering, to name a few, were involved in the advancement of technology [24]. However, according to Hoc [24], in these work situations the user mainly controlled the computer and the work was mainly passive.

In comparison, in Industry 4.0, there are more complex, connected systems which are developed through automation. According to Bachman et al. [31] the term Human-Computer Interaction can be replaced by the term Human-Machine Interaction (HMI) as human-machine interfaces vary widely, from the control panel of a vehicle manufacturing plant, touchscreens of mobile devices, to robots on the factory floor and automated systems that a user interacts with. Currently, during Industry 4.0, the demand of Human-Machine Interfaces was amplified significantly as HMI's prove necessary for the control and supervision of systems and to observe and oversee the manufacturing process from a central location [33].

In order for the human worker to effectively perform these tasks, systems should be available and implemented to provide the user with guidance and an overview of the system. Such a system is referred to as a Supervisory Control and Data Acquisition system (SCADA). The advantage of a SCADA system is the graphic appearance it presents of the factory floor which allows the human operator to monitor and view the system status at any time during production [33]. With regard to the advancement and development of automation, it is important to distinguish between a SCADA system and HMI.

A SCADA system is an integrated system which is used for the control and monitoring of different aspects of industrial plants and manufacturing environments [34]. A SCADA system operates by working with signals that uses communication channels for providing the user with remote controlling of equipment for a specific system [35].

In comparison, HMI's provide an efficient means for communicating with hardware and can thus be considered as a subsection of a SCADA system. Researchers have defined HMI's in various ways [33], [14] and can be described as an interface allowing for the interaction between humans, machines and systems. Human-Machine Interaction (HMI) refers to the communication and interaction between a human and a machine by means of a user interface [36], [37] and intends to increase the interaction between the human and machine through various input devices [38].

In autonomous environments robots and machines are becoming more complex with tasks and activities becoming less structured and, as a result interaction with humans to complete these tasks, become less and less [19]. Humans need a way of instructing the machine what to do via an input device such as a mouse, keyboard, touch screen and switches, to name a few. Machines, on the other hand, should be able to update the human of progress and execution of commands by means of some output even if it is a status light or an alert that can be heard [39]. The designing of such interfaces is a challenge in the sense that the interface should be functional, logical, effective and satisfactory to use [9].

The growing complexity of autonomous systems and robots has led to the study of how humans interact with robots and how to design systems capable of achieving tasks where the human still plays a pivotal role in the completion of tasks [19], [39]. Input and output components are needed for interaction between humans and machines and such interfaces should be usable to the user.

Experts specializing in the design and development of Human-Machine interfaces have done extensive research in the designing of usable interfaces [29]. What works for an engineer does not necessarily work for the human that needs to interact with the machine. This promulgates the importance of Human-Technology Interaction.

2.2.4 Human-Technology Interaction (HTI)

Taking a human-centred approach to the advancement of technology, it becomes evident that the development of technology takes place in a social setting and is formed by the operational objectives and processes of usage [40]. Hancock and Chignell [41] argues that human factors are not an isolated design issue but a point of view to technological innovation and development that has an enormous influence on the economic success of technology.

Human-Technology Interaction (HTI) is an interdisciplinary research area that focuses on the development of products for human-environment interaction [31]. HTI refers to the interaction between humans and technology through hardware and software with any technology, such as computers, robots, machines, smart monitors and virtual and augmented reality [9].

Although augmented and virtual reality is already used in manufacturing, the technological advancements will allow companies to make more comprehensive use of this technology to provide workers with training, real-time information for improving of decision-making, work procedures and collaboration [5].

HTI encompasses the processes, actions and dialogues that a user engages in to interact with technology, whether it is a computer, machine or robot. It also implies the study of interaction between users and computers, deals with people, software applications, computer technology and the ways they influence each other and as such balance the human interface with information systems and other technologies [29].

In the Industry 4.0 era we encounter a wide variety of HTI – any time a human uses technology, there is some type of hardware and/or software involved that enables and supports interaction. HTI concentrates on the aspects in which technologies facilitate the interaction between the human and the environment [40].

An important goal of HTI is to develop protocols, guidelines and/or tasks and algorithms for autonomous systems to enable safe, direct, effective and trustworthy interaction with humans [19]. Figure 2.2 depicts the comparison between HCI, HMI and HTI whereby the current new technologies and trends are assisting in more than just Human-Machine Interfaces but have moved towards interaction and interfacing technology between humans and autonomous systems.

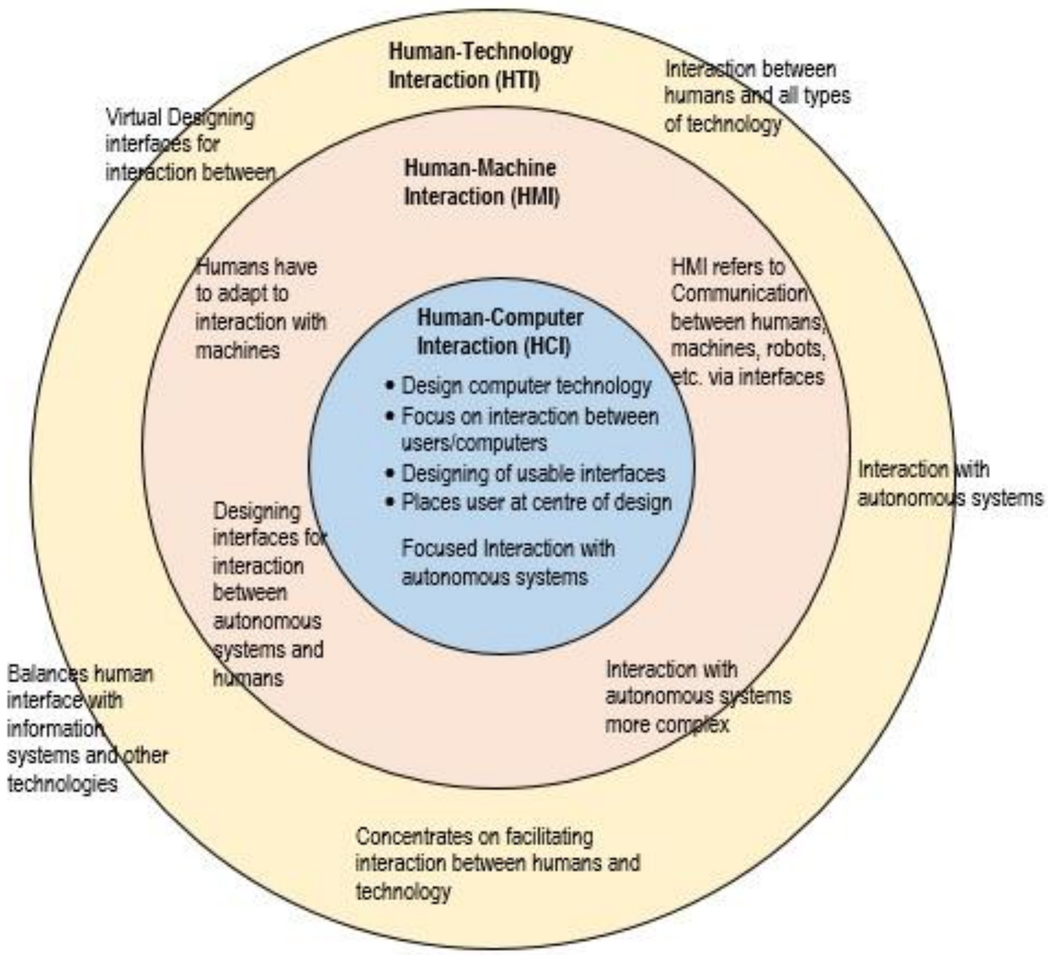

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Figure 2.2 Comparison between HCI, HMI and HTI

As the demands and allocations of humans and technology are rapidly changing, the study of information communication and cooperation between humans and technology becomes extremely important. This is referred to as collaborative decision-making.

2.3 Collaborative decision-making

With the evolution of Industry 4.0, more and more autonomous devices are moving out of laboratories and into the daily lives of humans to provide them with services and support the decision-making in different sectors ranging from intelligent food manufacturing, marine engineering to old age care [42].

Collaborative decision-making is an approach being used to facilitate efficient science-based decision-making [43]. In the Industry 4.0 environment, designers, technical practitioners and users need to work together to articulate the wants, needs and limitations of the users of autonomous systems to enable the creation of systems that address these elements.

Collaborative decision-making means to work together with someone on something to reach a common goal [44]. A team is formed when humans and machines work together on a mutual task where a team is defined as a small number of participants with similar skills who are dedicated to a shared goal for which they hold themselves responsible [45].

In a collaborative environment, the team members should know the intentions of the other team members and what they are doing. In HTI it will usually be the human who states the goal while the system must assist the human to take on the task and work toward reaching the common goal [45].

A common fear that Industry 4.0 has brought about, is the fear of job losses. However, advocates of Industry 4.0 give some reassurance that workers will be trained and re-skilled to work alongside automated machinery [45]. In the collaborative decision-making environment, Industry 4.0 systems will be able to complement tasks and activities performed by humans and also perform many tasks that go beyond what humans can do [46].

Realistically, some jobs will decrease, while others will grow and many occupations will change as requirements for more and new skills becomes necessary [46]. Re-skilling of workers will become a reality as they will have to adapt to systems that become progressively proficient in the workspace [24].

An example of collaborative decision-making is based on work done by Klumpp et al. [4] where three methods were focussed on to determine the fundamental role of Human-Machine Interaction (HMI) in automated environments in production logistics and in the Industry 4.0 environment [4].

The research emphasized HMI in connection with effective cooperation between workers, automated robotics and transportation systems. First using only the human in the decision-making process, secondly, only the robot and thirdly a hybrid of the human and the robot were executed for testing of the hypothesis.

The results yielded from this particular research [4] was that the acceptance level was the highest where humans and robots were equally cooperating during the decision-making processes rather than only robot- or human centred methods [4]. Designers and software engineers should aim for a collaborative design process for the design of interfaces that can be utilized in the controlling, monitoring and collection of data in an autonomous environment.

2.4 Potential models of HTI

This research uses the case study of an automated water bottling plant, as mentioned in Section 1.4, for the creation of a division between the set of jobs best executed by the autonomous system as well as the human related to the factory setting of the water bottling plant. Two potential models for collaborative decision-making are proposed in HTI allowing several alternatives. The two categories are machine only and a combination of human and the machine (hybrid).

2.4.1 Machine Only

This is the state that the case study is in its present status. In this scenario, the system is in full control of the allocation and execution of tasks, thus the human will have to adapt to the actions of the system. The automated water bottling plant will generate a flexible interactive mode for the improvement of system efficiency and operation safety.

In many cases, an autonomous system's actions are characteristically defined and can be displayed using similar one directional communication channels [7].

Planned system actions can be conveyed to humans via portable devices e.g. virtual or augmented reality glasses. This will allow the human to pay attention to the activities that the autonomous system is executing and pay attention to any possible errors or safety issues that may happen. The human will not be interfering with the activities performed by the autonomous system, unless intervention is required.

2.4.2 Combination of human and machine

The second option is to implement a combination where the human and autonomous system have equal responsibility with communication channels for planned actions in both directions – from the human to the system and from the system to the human. This approach can be described as collaborative decision-making as defined in Section 2.3. Humans need information on the intentions of the autonomous system and in turn, the autonomous system need information from the humans in the relevant environment for decisions to be made collaboratively. A combined approach may assist humans and machines, systems and robots to work together, but there are still many research questions that need answering before such a conclusion can be reached.

2.5 Limitations of Existing Research

This specific study focusses on investigating and establishing the importance of human intervention in a collaborative decision-making process for the optimum completion of tasks performed by an ICT enabled Smart automated manufacturing system. The aim of the research is to develop a protocol or guidelines and/or tasks that are best performed by a machine, by a human and a collaboration between the human and machine.

As mentioned in Section 1.1, at the time of writing this thesis, it became apparent that there exists limited research on how a collaborative decision-making process can be established such that the worker's acceptance and adjustment to the process is taken into consideration.

An important aspect that should receive some attention is how the interaction and communication of the human operator within the automated process can become part of the production process control loop [21]. According to Kruger, et al. [47] a close collaboration between the worker and automated system is required for the variability and adaptability of the assembly and production processes. The study done by Kruger, Lien and Verl [47] gives a survey about available technologies and different forms of Human-Machine cooperation in an assembly process and the support thereof. Both sides, that is humans and machines, have strengths and weaknesses and it is argued that the collaborative approach should make use of both sides during the production process. This study highlights the benefits of a close collaboration between the human and automated system, but lacks any usable guidelines or principles where the human is best suited and where the machine is best suited in the process.

Another relevant study done by Muller, et. al [48], identified that automation of processes are at the centre of the emerging Industry 4.0 environment although, as mentioned in Section 1.1, several assembly processes in manufacturing are nevertheless making use of mixed environments where human operators still manually carry out many of the assembly process tasks. Muller, Vette and Mailahn [48] suggest that, through innovative opportunities of using human-robot cooperation, a skills-based distribution of tasks can be implemented to address these challenges [48].

The study presented task assignments to a human and a robot by employing a process-dependant approach. In order to bring a sense of balance between the skills of human and robots, a thorough skills analysis of both humans and robots were assessed to take into account the features of the needed process or product [48].

An example of an assembly process in the aircraft industry was used to validate the method applied in the study. A comparison was done between the skills of the human and those of the robot in executing of tasks in the light of the conditions to be met in the production process. During the study it was found that there existed a lack of the obtainability of human-robot cooperation equipment and guidelines [48] which concluded that skills comparison and basic guidelines on tasks and/or actions, pertaining to a human and a robot, is vital for task assignment.

Garcia et. al [49] researched how to include a human-in-the-loop Cyber Physical System for collaborative assembly in Smart manufacturing by bringing the human decision-making capabilities into the control loop of a Smart manufacturing system. In this study a Natural Human-Machine Interface (NHMI) was introduced allowing the human to control, direct and collaborate with an industrial robot during execution of tasks. As discussed in Section 2.2.1, greater levels of complexity arises in Industry 4.0 which ultimately has an impact on the work that is done by human operators – occupations that require highly skilled workers will increase while low-skilled work will decrease [49]. Garcia, et.al suggests an approach of bringing the human-in-the-loop for allowing an explicit allocation or transferring of human skills to the control loops of a CPS.

The aim of this specific research was to create a framework for testing and validating some examples of potential human-in-the-loop control and to synchronize and work together with CPS in a collaborative environment. However, in this study there are no guidelines or principles provided for the human-in-the-loop or CPS allowing any decision-making capabilities [49], although the importance of bringing the human-in-the-loop was highlighted.

As mentioned previously in Section 2.2.3, Human-Machine Interfaces are without any reservation one of the most inherent components of an automated system [21], even though it comes with major concerns about aspects such as safety, maintenance and human operator awareness. This is according to Ponsa et.al [21] that states that even though human manual control in automated systems are being replaced with automatic controllers, human beings are essentially still required for modification, supervision, maintenance and enhancement of such automated systems [21].

System complexity increases dramatically with automation which leaves the challenge of maintaining operational skills in an automated environment [21] when an abnormal situation should occur and human intervention becomes necessary. The study done by Ponsa, et.al [21] identified a gap in the design for a huge number of HMIs, allowing for supervision, monitoring and communication of large scale systems by implementing the operational modes of the automation level into the interfacing system. The researchers investigated how the human operator will be able to enter the control loop as both the human operator and the machine contributes to the completion of a process.

A possible solution was to introduce the GEMMA guide approach [50], which is an approach for dealing with unravelling difficult tasks in automated problems, as a recommended taxonomy for the introduction of the human into the automated process in complicated industrial or academic fields [21]. A case study was used for the presenting of operational guidelines as well as the application of the design of interfaces in automation but there is no evidence to indicate as to which tasks should be allocated to human operators and/or to the automated system in the specific case study.

The major shortcoming of these studies indicates that there is limited research on designating where the human operator is best suited in the automated process and where the machine should take full control. It is also evident that there are no existing guidelines as to where in the production process a collaboration between the human and machine is the best suited scenario for a specific case. This research aims to develop a protocol or guidelines and/or tasks that are best performed by a machine, by a human and a collaboration between the human and machine.

Chapter 3: Research Methodology

3.1 Introduction

This chapter focuses on the research methodology employed by the researcher, whilst also providing a justification for the selection for this particular methodology for the study by addressing the challenges described in the limitations to the existing research in Section 2.5. Furthermore, the ensuing sections will give an overview on the developing of a generic protocol for collaborative decision-making and also of the research methodology applied, a description of the case study selected for the study and how the chosen experimental data collection methods were utilized whilst conducting the research.

3.2 Research Design and Methodology

The aim of this research, as stated in Section 1.2.3, is to investigate and establish the importance of human intervention in a collaborative decision-making process for the optimum completion of tasks performed by an Information and Communication Technologies (ICT) enabled Smart automated manufacturing system and propose a protocol to determine the tasks/actions best performed by machine, by a human and a collaboration of human and machine.

In achieving the objectives specified, the study will make use of a research design method known as a single-case experimental study.

3.2.1 Description of a single-case experimental study

A single-case experimental design, also denoted as single group pre- and post-test research design [51], indicates a set of experimental measures for the testing of a product, process or other intervention through implementation of a limited number of cases with the aim of testing for efficiency [52].

A single test experiment refers to a set of experimental methods that can be used to test the effectiveness of a product, process or other intervention [52] and comprises repetitive measurements, observations, specific data analysis and statistics [52]. Single test case research involves a carefully designed study prior to the start of the experiment and therefore are true "experimental" research designs with specific goals in mind [40],[52].

3.2.2 Motivation for using a single-case experimental study

A single-case experimental study is performed with three specific goals. The first is to test if any new inferences can be made, secondly it is to 'test' a theory and thirdly to prove a theory [53]. Exploratory experiments are done to test the first case, and have little structure which involves exploring an idea to see what can be learned, whereas testing a theory involves conducting a limited experiment and investigating whether the theory holds for some specific cases [53]. The third type of experiment is to prove that the theory holds and that all potential doubts are removed. This study implements the third type of experiment namely to prove a specific theory that will be discussed in detail in the next section.

3.2.3 Setup of the single-case experimental study

A single test case will be employed to prove the theory, which is that the completion time for orders received, will be optimal when the human and the machine collaborate for the completion of the production process.

For this purpose, two different scenarios will be introduced to determine the impact of collaborative decision-making in the automated system namely the machine only and secondly a collaboration between the machine and the human operator. The machine only scenario will be the control case, as the system will complete the production process in automated mode without any human intervention, whereas the Human-Machine collaboration will be used as the test case.

Based on the single-case experiment intended for this study, a case study needs to be introduced whereby the two types of experiments will be set out and used to compare the two scenarios mentioned. The purpose of the experiments are to prove the theory that human intervention in a collaborative decision-making process contributes to the optimum completion of tasks performed in an ICT enabled automated Smart manufacturing environment and put forward a protocol to determine the tasks or actions best performed by a human, a machine or a collaboration between the human and the machine.

3.3 Developing a generic protocol for collaborative decision-making

The formation of evidence through collection and analysis of data is fundamental to any process, whether in production, pharmaceuticals, businesses and manufacturing to provide a high degree of reassurance that a process is capable of meeting pre-determined specifications and quality outputs [54]. This can be achieved by making use of specific protocols developed for a certain process. A protocol can be defined as the proper procedures used to implement a process [55] and for this study a protocol for collaborative decision-making in an automated environment will be developed.

A key component in developing a protocol for an automated environment is defined by the Overall Equipment Effectiveness (OEE) which is a Key Performance Indicator (KPI) used to measure equipment efficiency and performance [56]. The metric of OEE as a KPI were introduced in 1988 by Nakajima [56] for measuring the equipment productivity in a manufacturing system and has been extensively recognized by companies for implementing "lean manufacturing and maintenance programs for measuring the actual performance of equipment" [56], [57].

3.3.1 The Overall Equipment Efficiency (OEE)

OEE is the gold standard for determining manufacturing productivity and efficiency [58]. A lot of information is provided in one number for the OEE score to define efficiency [58]. OEE is a benchmark to correlate production to industry standards, for specific apparatus or other processes using the same equipment [59].

By its definition and extent, OEE continues to be a tool in supporting decision-making for responsive control and pre-emptive intended improvement of equipment efficiency in the long-term [60].

According to Trout [58], standard benchmarks are as follows:

- An OEE score of 100 percent is considered perfect production, meaning you're only manufacturing quality parts as quickly as possible with no downtime.
- An OEE score of 85 percent is considered world class for discrete manufacturers and is a sought-after long-term goal.
- An OEE score of 60 percent is typical for discrete manufacturers and shows there is considerable room for improvement.
- An OEE score of 40 percent is considered low but not uncommon for manufacturers just starting to track and improve performance. In most cases, a low score can easily be improved through easy-to-apply measures [58].

Furthermore, "manufacturing operations with an OEE score above 85% are in the top level" [56]. Even the best machines eventually require maintenance or retooling, therefore it is almost impossible to sustain an OEE score of 100% [56] .

There are a number of important terms to know when OEE is to be calculated, which are the following:

- **Fully Productive Time -** Production time after all losses are subtracted
- **Planned Production Time -** The total time your equipment or system is expected to produce
- **Ideal Cycle Time** - The time it takes to manufacture one part
- **Run Time** - The time your system is scheduled for production and is running
- **Total Count** - The total of all parts produced including those with defects
- **Good Count** - Parts produced that meet quality-control standards
- **Good Parts** - Parts produced that meet standards and don't need to be redone
- **Availability** – takes into account planned and unplanned stoppage time.

- **Performance** – takes into account the number of times there are slowdowns or brief delays in production.
- **Quality** – refers to the manufactured product that does not meet the quality control standards.[58], [59].

In accordance with Trout [58], there are two main methods to calculate OEE:

- **Equation 1:** The ratio of fully productive time to planned productive time is the way to calculate OEE. The formula looks as follows:

  (Good Count x Ideal Cycle Time) / Planned Production Time = OEE

- **Equation 2** for OEE calculation is based on three factors namely A*vailability, Performance and Quality.* This calculation gives as result the OEE score indicating how well the production is doing while providing three numbers (availability, performance and quality) showing what caused any losses. The formula to calculate the OEE score is:

  Availability x Performance x Quality = OEE

Taking into account the case study for this research and the requirements to calculate the different parameters, Equation 1 is the more suitable method for calculating the OEE score for this case study.

In accordance with a systematic literature review done by Carmen, et. al [56] it was found that over time, modifications have been done on OEE applications depending on industry needs; some authors have slightly altered the original formula, whereas other suggested new formulas [61]. Many industries have tailored OEE to fit to their specific requirements [56], [61]. The OEE structure has been used to build different models for domains like sustainability, line manufacturing, resources, assets, conveyances and ports [58].

The OEE that will be applied to this study is a model developed over time and slightly altered, as mentioned above, namely “Overall Equipment Effectiveness of a manufacturing line” which measures the performance of an automated line in the production system [56]. The OEE for the manufacturing line identified for this study has the same characteristics and parameters as in the case study utilized in this research. A list of models based on OEE can be seen in Appendix C, as identified by Carmen, et.al [56] during a systematic literature review performed on Overall Equipment Effectiveness and the different approaches utilized for equipment productivity and performance. Section 3.3.2 looks at the different steps for developing a generic protocol.

3.3.2 Steps for developing a generic protocol

There are several steps involved in developing the generic protocol which includes the following:

Step 1: → Determine the average production time for the completion of one production cycle for a specific product.

Step 2: → Determine Overall Equipment Efficiency (OEE).

Step 3: → Apply the values found to the Statistical Analysis Software (SAS) code used to calculate the results.

Step 4: → Input the values for customer orders received into the SAS software program.

Step 5: → Calculate the Total Time to Manufacture (TTM) one batch of customer orders in fully automated mode.

Step 6: → Calculate the Total Time to Manufacture (TTM) one batch of customer orders in the human intervention mode.

Step 7: → Apply the OEE score to the automated process and to the human-machine collaborative process.

Step 8: → Assess results for TTM’s of both approaches to establish when the machine are in full control and when human-intervention is needed in the production process.

3.4 The Experimental Setup

The method that will be followed for the execution of the single case experiment, is illustrated in Figure 3.1 below as a flowchart. The flowchart indicates the two approaches that will be carried out, with the fully automated approach used as the control case and the collaborative decision-making approach as the test case.

In executing the single-case experiment, collaborative decision-making will be introduced by utilizing the case study of an existing, fully automated water bottling plant on which the steps listed in Section 3.3 are to be implemented.

Sections 3.5 and 3.6 will give an outline of the water bottling plant as well as a brief overview of the operation of the existing plant that was utilized as the case study for this research.

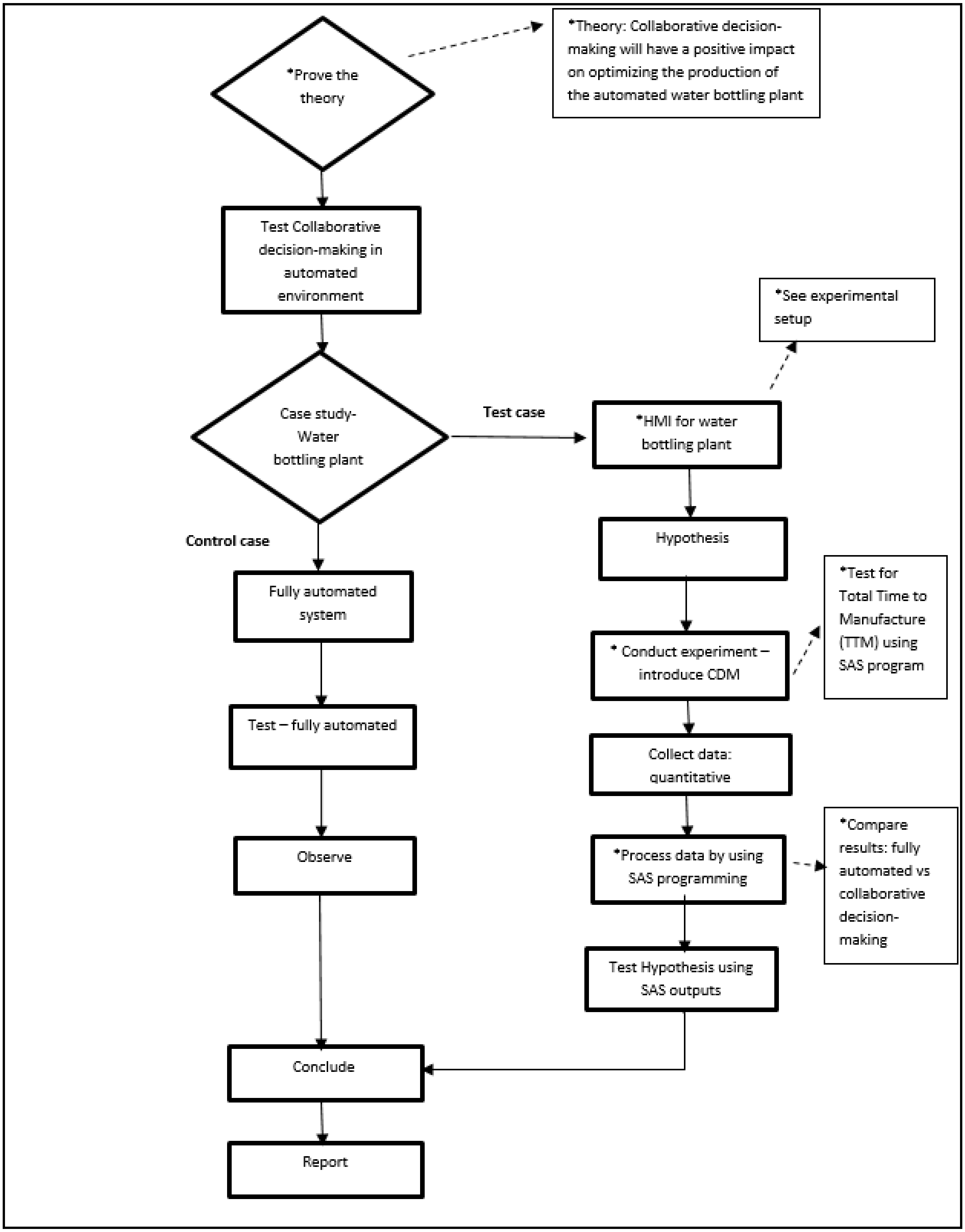


Figure 3.1 Flowchart indicating the experimental research approach

3.5 An overview of the Water Bottling plant case study

As alluded to previously, the study will employ the case study of an automated water bottling plant to conduct research on Human Technology Interaction for collaborative decision-making. The water bottling plant was a concept that was put forward by the management of the Central University of Technology (CUT), Free State to produce their own bottled water for internal use.

An economic feasibility study done in conjunction with the technical study determined that the water bottling plant, hence forward referred to as the plant, needs to produce bottled water in 330ml and 500ml sizes. A 3-dimensional printed model of the completed plant [13] is shown in Figure 3.3. As depicted in Figure 3.2, the plant has three major units being the source and tank unit (A), the bottle manufacturing and storage unit (B) and the water filling unit (C).

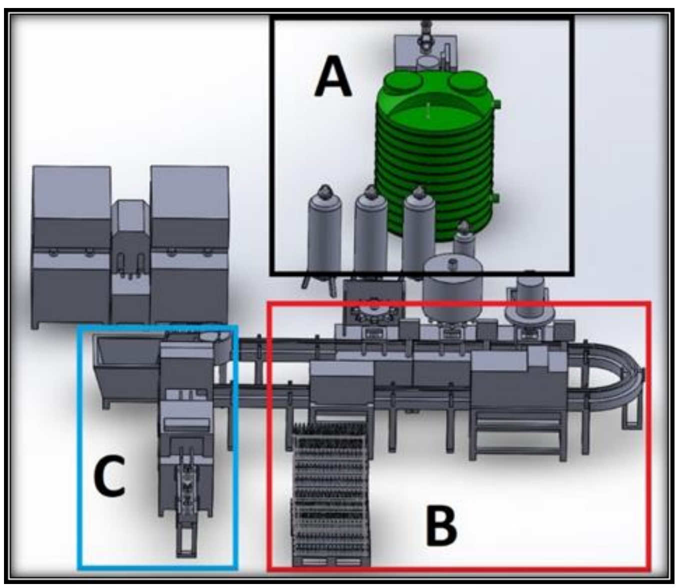


Figure 3.2 A 3-D printed model of the completed plant [13].

The 3D model depicted in Figure 3.2 was successfully modelled in Simulink and optimized using MATLAB as part of the technical feasibility. The ordering of the bottles are made online and stored on a cloud server where the MATLAB program can access and process the data to start filling the bottles [62] . An interactive user interface has been developed to receive input to the model via an online web application [12] where customer orders are placed for the filling of 330ml or 500ml water bottles.

Customers are required to complete their personal details, the desired bottle size and the required date of delivery. The information is captured on a cloud server from where the MATLAB program access and processes the data to initiate the water filling process [12]. Figure 3.3 shows the user interface of the web application used for customer orders.

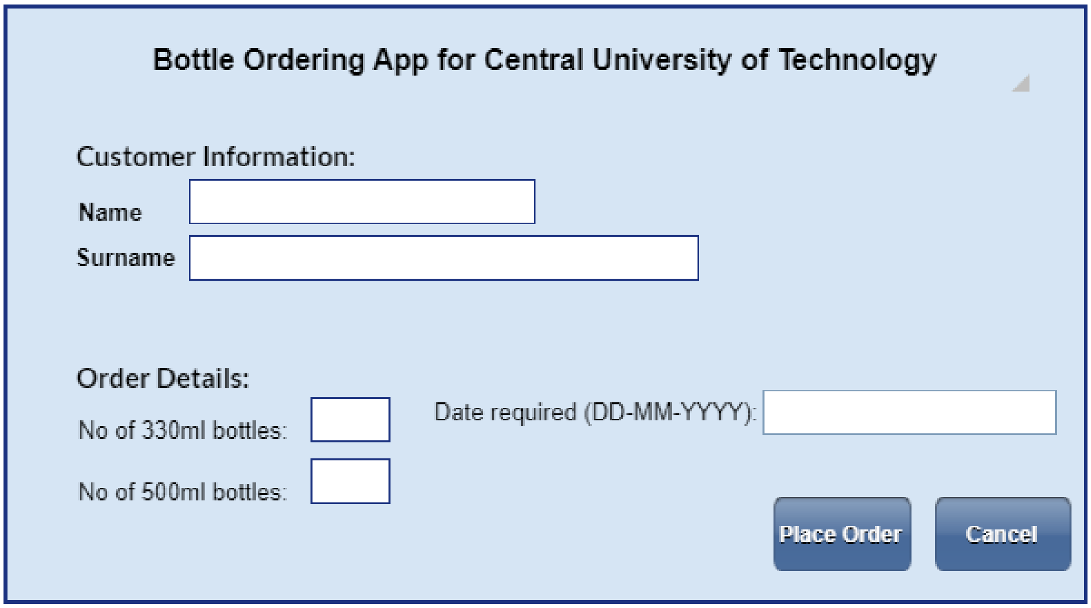


Figure 3.3 The user interface of the customer order application [12].

Based on the requested date of completion and the status of constraints like amount of water available and number of bottles in the storage, the optimization model executes the order. The optimization model is practically executed using three Smart Manufacturing Units (SMU's) driven by a combination of sensors and Programmable Logical Controllers (PLC's) which is portrayed in Figure 3.3. The proceeding section will take a closer look at the working of the water bottling plant highlighting a description of SMU's, followed by a more detailed working of each SMU in the water bottling plant.

3.6 Operation of the Water bottling plant

As stated in the background, the plant utilises three Smart Manufacturing Units (SMU's) driven by Programmable Logical Controllers (PLC's) with sensors and actuators as depicted in Figure 3.4.

The water bottling plant is split into three sections which is run on the SMU's which consist of a unit for the filling of 330ml or 500ml bottles, the capping unit where the bottles are capped and a third unit for the packaging of completed orders.

Refer to Appendix E for pictures of the physical water bottling plant used in the case study for this research.

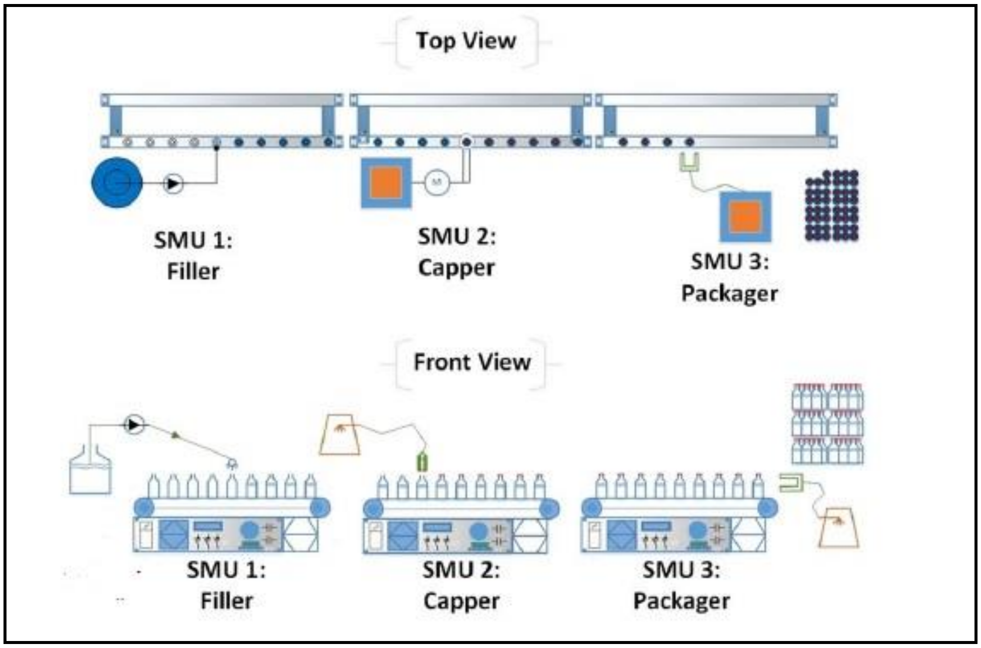


Figure 3.4 The layout of the Smart Manufacturing Units in the plant [12].

The following sections will discuss the three SMU's used in the plant as well as their operation in more detail.

3.6.1 Smart Manufacturing Units (SMU's)

Smart Manufacturing, as discussed in Section 2.2.1, is one of the key pillars of Industry 4.0 [63] which comprises the integration of production and manufacturing resources with computing platforms. Smart manufacturing make use of networked data, information and communications technologies (ICTs) for leading manufacturing operations [16]. This allows for the creation of production orders in single production line models that can be modified and customised in the case of rapid design changes [64] or complex specific customer orders.

In order for the machines to adapt to complex and rapid changes in customer ordering scenarios, they need some form of intelligence to enable informative and smart decision-making during the production process.

The technology that enables Smart manufacturing in the Industry 4.0 environment is Smart manufacturing Units (SMU's) [63] where the units possess characteristics that are able to process decisions and allow for customised configuration and development in the automated production process [65]. The control units for the SMU's used in the plant is the Siemens S7-1200 modules and the operational working of the three SMU's in the plant will be discussed in the following sections.

3.6.2 SMU1

The task of filling the water bottles is allocated to SMU1, which receives customer orders via the online web application. Customers are able to specify whether they require the filling of 330ml or 500ml water bottles, the number of bottles required as well as the date of delivery preferred. The water bottling process starts with SMU1 that initially detects the bottles lined up for filling. Detection of the new bottles added to the production line is enabled by using an attached camera module for image processing for distinguishing between 330ml and 500ml water bottles [63].

Once the bottle size to be filled is established, the correct bottle is selected by SMU1 from storage and filled as per order [63]. The detection protocol utilized in the production process allows for the unscheduled addition of bottles, allowing for Smart manufacturing intelligence to balance out any occurrences of irregular feeding to the production line [63]. Furthermore, the required filling percentage of each bottle can be verified by using this system, but the technical information regarding the communication protocols utilized, falls beyond the scope of this study.

3.6.3 SMU2

SMU2 is assigned the task of capping the water bottles. Since there are two sizes of bottles that can be filled, the height at which the bottle caps are to be fastened can be communicated to SMU2 by the central server to the responsible machine. SMU2 queries the central server on the bottle height while SMU1 determines the type of bottle to be filled and passes on the information to SMU2 [63]. It is important to note that both the 330ml and 500ml bottles use the same size of caps.

As for SMU2, a similar situation to that of SMU1 was taken on for controlling of the machine, with the addition of a guided rail arm that can be programmed to move in a *x*-*y* axis. In this case it is used only in the *y* axis (moving downwards) and is attached to SMU2. The arm is fitted with a rotary motor which in turn is connected to the capper. Communication is sent from SMU1 to SMU2 as well as the guided rail arm, allowing for preprogrammed movements for the fitting and capping of the correct caps for the bottles in production.

3.6.4 SMU3

The task of SMU3 is to package the water bottles according to order and completion. A unique radio-frequency identification (RFID) tag is attached to every bottle for the tracking of production information by each machine. This allows SMU1 to fill bottles by order and the tagging of the water bottles allows SMU3 to read the RFID and pile the bottles corresponding to orders received [63].

SMU3 will be able to set aside orders and package them as they are received if it may be the case that bottles are initially filled by type and not by customer order. It is important to note that SMU3 does not form part of the study as it provides no real contribution to this particular study. A different study is in progress where more technology will be integrated to ensure that the packaging section is fully functional. Therefore, SMU3 is beyond the scope of this specific research, hence it will not be discussed, although it can be seen as part of the complete automated plant.

The proceeding sections will discuss the two approaches that will be used in executing the single-case experimental setup, namely the machine only and secondly the Human-Machine collaborative approach. Thereafter, the experimental setup and how it is executed and applied to develop a generic protocol for collaborative decision-making in an automated environment, will be discussed in Section 3.10.

3.7 Machine only

For the machine only scenario, the automated system is responsible for completing the task of filling either 330ml or 500ml bottles in optimum time as orders are received via the web application referred to in Section 3.5. The optimization model considers several constraints, such as the number of orders received from the cloud, the water level in the storage tank as well as the number of 330ml and 500ml bottles and caps in storage for the completion and execution of the production process. Figure 3.5 depicts the top view of the fully automated process. No human intervention takes place unless maintenance or unforeseen issues arise.

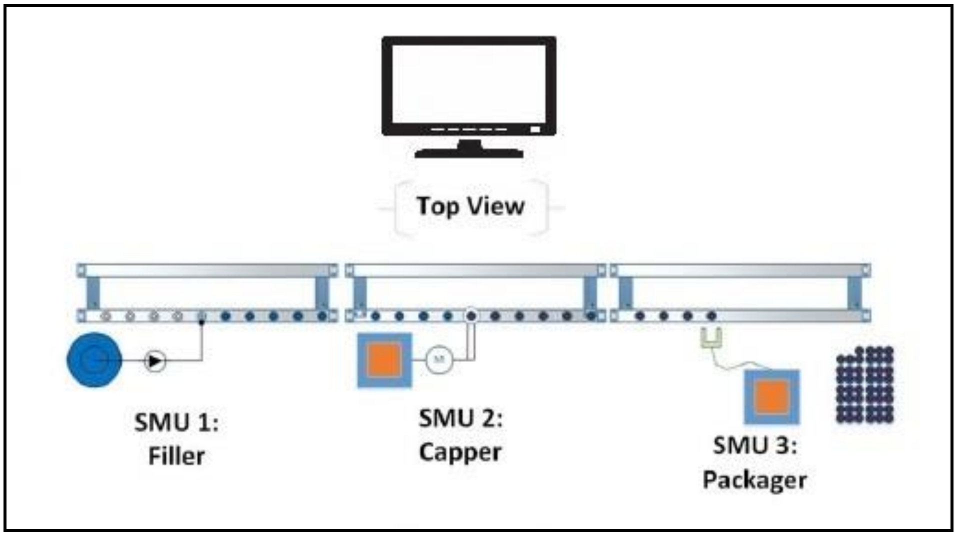


Figure 3.5 Layout of the fully automated production process.

3.7.1 Automated experimental process – the control case

For the control case, the machine, as illustrated in Figure 3.5, exclusively makes all the decisions. Table 3.1 summarizes the working of the different SMUS's indicating the effect on the production process when specific constraints are encountered during the fully automated process.

Table 3.1. Summary of plant working in fully automated mode.

Constraint	SMU1		SMU2		Process
Limitation at 100%	Water level in storage tank OR Bottles in storage	**OR**	Available caps in feeder		Production starts at pre-set speed
Limitation reaches 50%	Water level in storage tank OR Bottles in storage	OR	Available caps in feeder	OR	Production pauses as machine waits for water level, bottles or caps to increase to 100%.
Limitation reaches 25%	Water level in storage tank OR Bottles in storage	OR	Available caps in feeder	OR	Production stops seconds while waiting for water level, bottles or caps available to increase levels from 25% to above 50%.
Limitation increases to above 50%	Water level in storage tank AND Bottles in storage	AND	Available caps in feeder	AND	Resumes production

The system is programmed to automatically slow down or pause the production process, as shown in Table 3.1, when the water level reaches a certain level, when the number of bottles are low or when the capping feeder runs low to ensure that the production process does not come to a complete halt. The production process resumes as soon as the capacity of the water tank, the number of bottles or number of caps increases to above 50%.

For the execution of the automated process experiments, multiple sets of customer orders for filling of water bottles will be placed via the online Web application whereby the Total Time to Manufacture (TTM) will be determined for the completion of each customer order by executing the SAS program which will be discussed in Section 3.9. The SMU’s to which the model is linked, provides feedback on the completion of orders received from the cloud and the resulting data will be recorded for evaluation purposes regarding the subsequent output using the Human-Machine collaboration approach.

3.8 Collaborative Decision-Making approach

3.8.1 Introducing a HMI to the manufacturing process

As discussed in Section 2.2.3, a SCADA system will be used to provide the different configuration options stated earlier for the study. A SCADA system is an integrated control system that utilizes computer functions, graphical user interfaces and networked data communications [66] for the control, data acquisition and monitoring of different aspects of industrial plants and manufacturing environments [9],[38]. The SIEMENS Simatic HMI to be used in this study, is shown in Figure 3.6.

A SCADA system development environment will be used for configuring the PLC’s to enable communication with the HMI’s. A software development platform will be used to connect the HMI’s, SMU’s and the SCADA system for bridging the communication between the three devices to allow for standardized communication. The HMI is a subset of a SCADA system and it provides an effective way for the human operator for communicating with the hardware. The HMI in this study will be localized and focusses on collaborative decision-making.

Figure 3.6 The SIEMENS Simatic HMI used as the SCADA system for the case study.

3.8.2 Human-Machine Collaboration approach

In order to bring the human into the production process a Human-Machine Interface (HMI) will be developed and assigned for intervention by the human at SMU1 and SMU2. The HMI consists of an intuitive touch-based input screen whereby the human operator will be able to communicate with the system. The human will be able to stop, slow down or continue the production process using the HMI's. The layout of the collaborative approach indicating the HMI's connected to the SCADA system, is illustrated in Figure 3.7.

In the Human-Machine collaboration scenario, there are different places where the human can fit into the production line, such as at the placing of online orders, water filling (SMU1) or capping (SMU2) as depicted in Figure 3.7. allowing the human to intervene using the HMI's for making informed decisions during the production process.

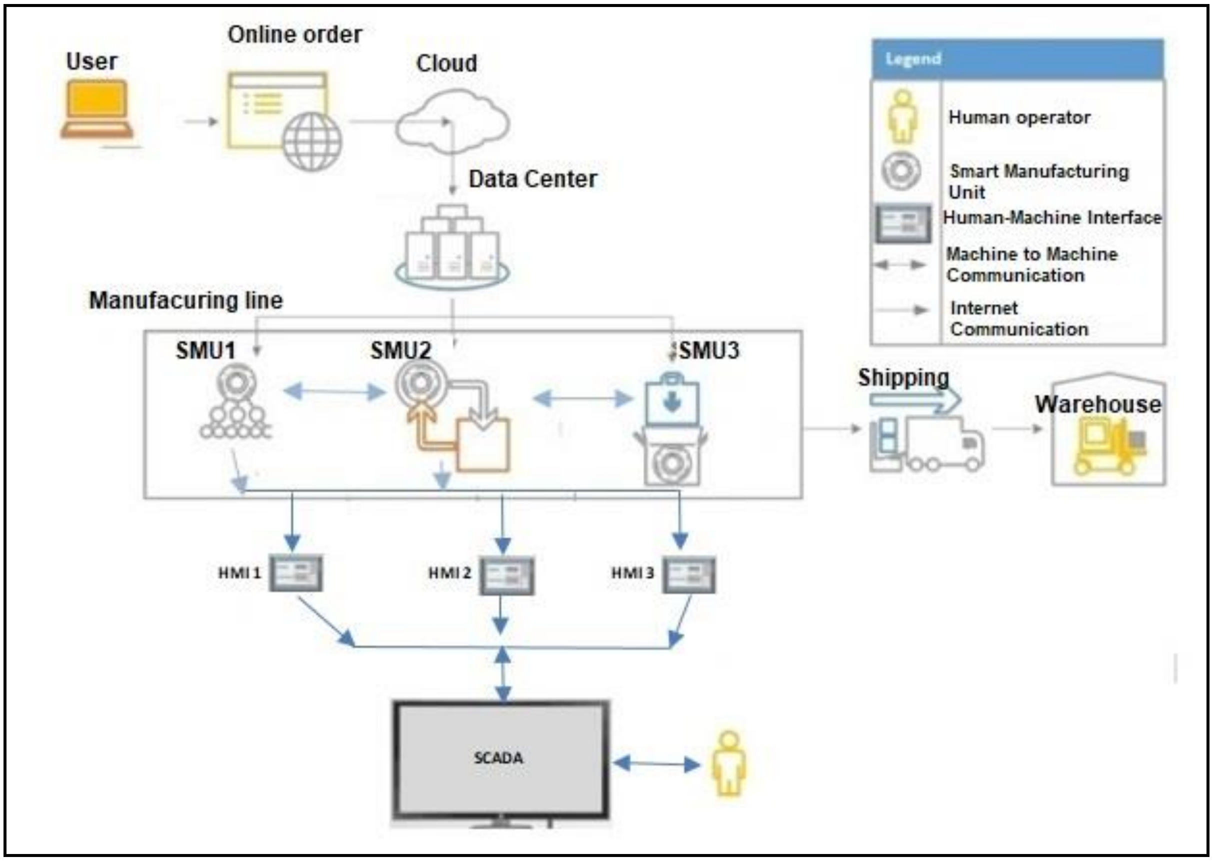


Figure 3.7 The production layout for the automated water bottling plant indicating the HMI's connected to the SCADA system.

3.8.3 Experimental setup of Human-Machine Collaboration – The test case

As explained in Section 3.7.1, the automated system has been programmed to create alerts when levels of water, bottles and caps, reaches 50% and again at 25%. By bringing the human operator into the control loop, informative decisions can be made by using the information and results generated by the SAS program.

Important to note is that no human intervention will be required when all the constraint levels are above 50% and the OEE score is above 90%. The results from the SAS program will be presented to the human and when necessary, the HMI will allow the human to intervene and make a decision to adjust the speed of production depending on the availability of water and/or water bottles. The human can also intervene when alerts are triggered when the bottle capping feeder reaches the specific constraints as indicated in Table 3.2.

In addition to the results obtained from SAS, the SCADA system will supply the human with an overview of the status of the system to enable the human to make informative decisions for the continuing or halting of the automated process.

Table 3.2. Summary of the collaborative decision-making process.

Alert	SMU1 with HMI 1	Human intervention	SMU2	Human Intervention	Production Process with human intervention
Test case 1: Limitation reaches 50%	Water level in storage tank OR Bottles in storage	Human has option to stop, continue, speed up or slow down production depending on orders that need to be completed	Caps in storage	Human has option to stop, continue, speed up or slow down production depending on orders that need to be completed	**Decision:** HMI indicates levels, human makes decision for production to continue at normal speed if orders can be completed with enough water, bottles or caps in storage
Test case 2: Limitation reaches 25%	Water level in storage tank OR Bottles in storage	Human has option to stop, continue, speed up or slow down production depending on orders that need to be completed	Caps in storage	Human has option to stop, continue, speed up or slow down production depending on orders that need to be completed	**Decision:** Human can see via HMI where constraint levels are and what is available. Make decision to continue production, stop or slow down if orders can be completed with enough water, bottles or caps in storage.
Test case 3: Limitation **increases** to above 50%	Water level in storage tank AND Bottles in storage	Human allows production to continue	Caps in storage	Human allows production to continue	Resumes production at normal speed

3.9 Definition of Statistical Analysis Software (SAS) used for executing the single experimental case

Statistical Analysis System (SAS) is an integrated system of software products which permits programmers to perform information retrieval and data management, statistical analysis, report writing, graphics, business planning, forecasting, and decision support, among other services [67] . SAS will be used for determining the output of the fully automated approach vs the Human-Machine collaborative approach by accurately predicting which processes in the manufacturing process is best done by Human-Machine collaboration and which are best left to be completed by machines only. To achieve this result, the OEE score, as discussed in Section 3.3.1, is applied to the SAS program code.

The following sections will describe how SAS was used for the execution of the data as presented in the different cases of customer orders, whereby some guidelines can be derived from as stated in the research objectives. This will be presented in Chapter 5 after the validation and analysis of the data gathered. A flowchart of the working of the SAS program is indicated in Figure 3.8.

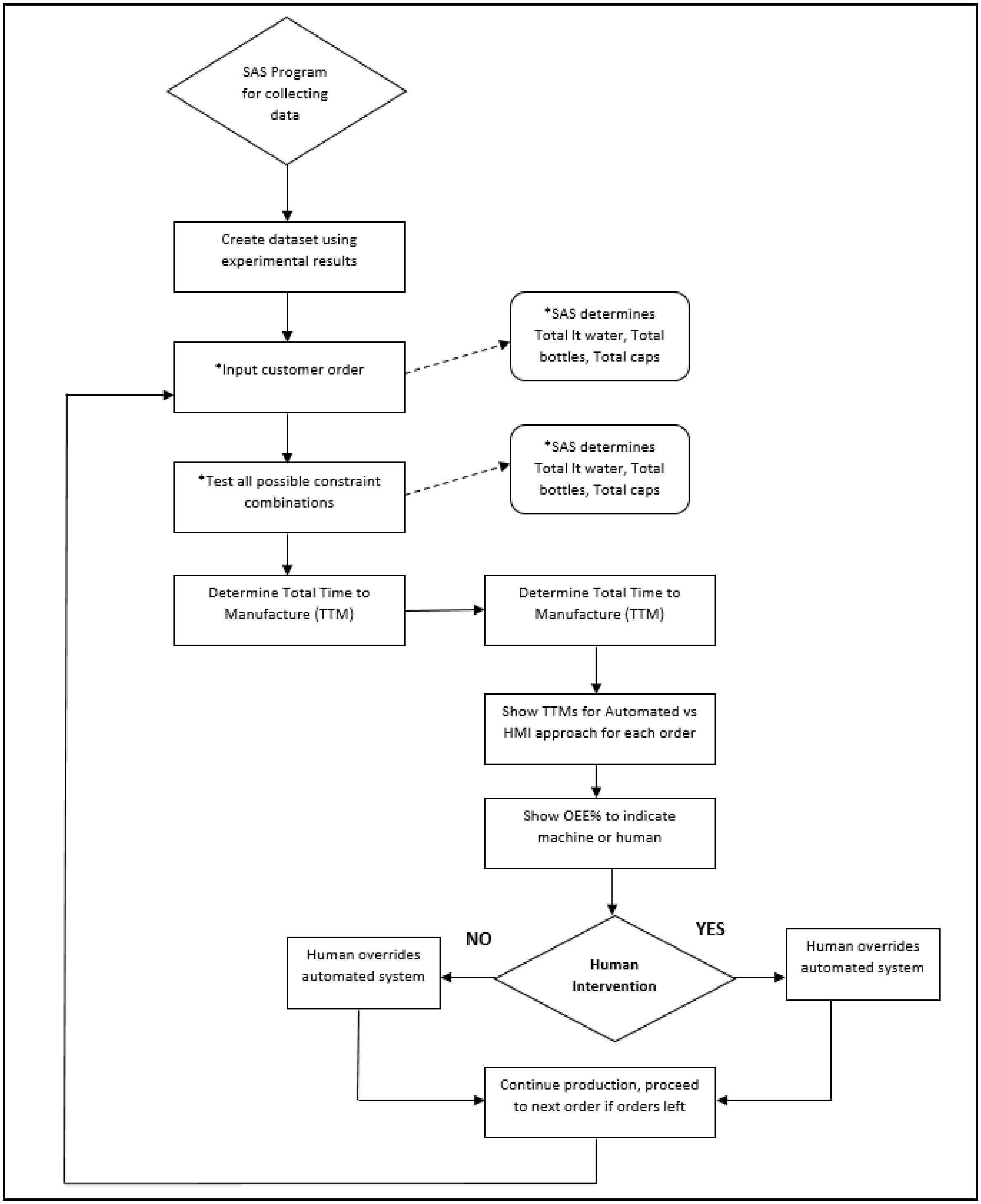


Figure 3.8 Flowchart indicating the flow of the SAS program

3.10 Execution of the Single Case Experiment

In order to evaluate the effect of introducing collaborative decision-making to the automated system, a Human-Machine Interface (HMI) will be developed and attached to SMU1 and SMU2 of the water bottling plant, allowing for a collaboration between the human and machine. As stated previously, two approaches will be introduced namely the machine only and secondly a collaboration between the human and the machine. Section 3.7 describes the operation of the automated system with the machine in control (control case) followed by Section 3.8, which describes the operation of the Human-Machine collaborative approach (test case).

Based on the steps for developing a generic protocol for collaborative decision-making as described in Section 3.3, it should be noted that Steps 1 – 5 in the following sections are executed in the fully automated approach while Steps 6 – 8 are performed in the collaborative decision-making approach.

As explained and illustrated in Table 3.1 and Table 3.2 the constraints and variables were highlighted, as these are the restrictions or limitations that have to be taken into consideration in the SAS programming for determining the different production times. Using SAS, the production time or Total Time to Manufacture (TTM) for both the automated approach and the collaborative approach will be determined. The main aim is to determine whether the production time will be optimized when the human and machine work in collaboration for completing a set of orders as this research aims to establish the importance of human intervention in a collaborative decision-making process for optimum completion of tasks and providing a protocol with guidelines as to which tasks or actions are best done by a machine, a human or a collaboration between human and machine.

3.10.1 Executing the fully automated approach

The system is programmed to automatically slow down or pause the production process when the water level reaches a certain level, when the number of bottles are low or when the capping feeder runs low to ensure that the production process does not come to a complete halt. The production process resumes as soon as the capacity of the water tank, the number of bottles or number of caps increases to above 50%.

As mentioned in Section 3.7.1, the automated mode of the plant is the control case where the machine executes the entire production process without human intervention. In order to determine the TTM for the process, the first important step was to determine the average time it takes to fill one 330ml bottle and one 500ml bottle.

3.10.2 Step 1: Determining the average time to fill one 330 ml and one 500ml bottle

To determine the average time, multiple tests were done in real time where the time to fill a bottle for production was timed and recorded. The timing commenced when the bottle on the conveyor belt started moving towards SMU1 for filling and then towards SMU2 for capping the bottle. This process is indicated in Figure 3.9.

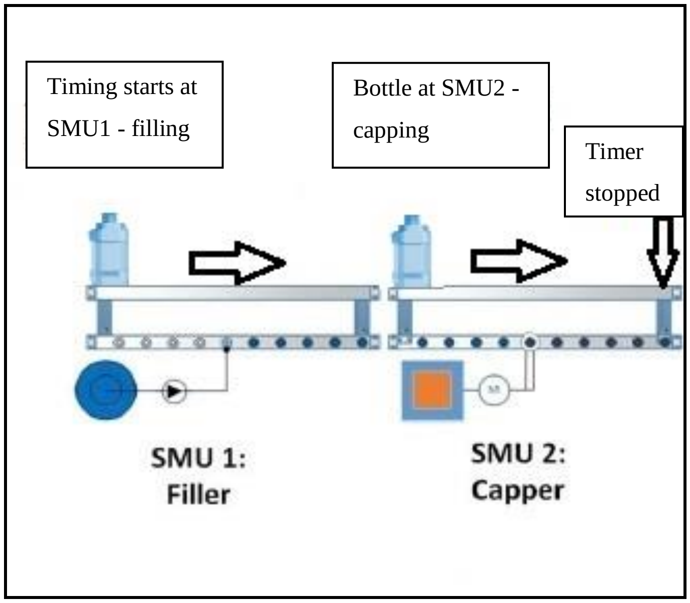


Figure 3.9 Determining of the time for filling and capping one bottle.

It should be pointed out that the recording of the average times were done in real time on the existing automated water bottling plant. The recording of the timing of the process was done for both the 330ml bottles and the 500ml bottles.

After completing several tests, the total time for each individual round of 330ml bottles were added together where after the average time was calculated. The same process was done for the 500ml bottles whereby a conclusion was reached indicating that the average time to fill and cap a 330ml bottle takes 45 seconds, while the 500ml bottle takes 48 seconds to fill and cap. These results indicate the ideal scenario where the water level, bottles available and caps available are at 100%.

As the orders are filled and capped, the levels of the water, bottles and caps will start depleting which causes certain constraints to be met as described in Table 3.1. For purposes of executing the experiment it is important to note that when the water level reaches 50%, a delay of 15 seconds were recorded, as indicated in Table 3.3, during the production time for each 500ml or 300ml bottle. This delay was documented during the timing of the process in real time where it was discovered that it takes 15 seconds to replenish the water, bottles or caps levels to 100%.

A similar scenario happens when the levels reaches 25% when a delay of 30 seconds were measured while the machine waits for the levels of bottles or caps to be increased, or the water level is replenished to above 50% for production to resume. The time delay gets added to the average time for filling and capping the bottles once these scenarios occur, as indicated in Table 3.3.

It should be pointed out that the delays will only be triggered when the constraint levels reaches 50% or 25%, which means that for the first 50% of the filling and capping process there will be no delays during the production process. The same delay times will be included in the SAS program for determining the TTM for each order in the Human-Machine collaboration mode.

Table 3.3 Summary of real time results of the plant working in fully automated mode.

Constraint	SMU1		SMU2		Process
Limitation at 100%	Water level in storage tank OR Bottles in storage	**OR**	Available caps in feeder		Production starts at pre-set speed
Limitation reaches 50%	Water level in storage tank OR Bottles in storage	OR	Available caps in feeder	OR	Production pauses for 15 seconds as machine waits for water level, bottles or caps to increase to 100%.
Limitation reaches 25%	Water level in storage tank OR Bottles in storage	OR	Available caps in feeder	OR	Production stops for 30 seconds while waiting for water level, bottles or caps available to increase levels from 25% to above 50%.
Limitation increases to above 50%	Water level in storage tank AND Bottles in storage	AND	Available caps in feeder	AND	Resumes production

3.10.3 Step 2: Determine the OEE score

For the purpose of this case study, taking into consideration the requirements of each of the Equations explained in Section 3.3.1, Equation 1 is the more suitable method. In order to determine the OEE score, the following formula for Equation 1 and the parameters described in Section 3.3.1 will be used:

(Good Count x Ideal Cycle Time) / Planned Production Time = OEE

Good Count = Total no 330ml + 500ml bottles for customer order
Ideal Cycle Time = Average time of producing a 330ml + a 500ml bottle per cycle
Planned Production Time = Total Time to Manufacture a customer order

As alluded to in Section 3.3.1 an OEE score of 85% is considered world class for different manufacturers [58]. However, this study places the OEE at 90% which should be seen as a good benchmark for determining the efficiency and checking the veracity of the model as it also brings into factor the constraints such as the amount of water in the storage tank, the number of bottles and caps available for completing the customer orders. The plant utilized in this case study functions in a laboratory setup and thus the OEE score of 90% is used as the plant operates in ideal conditions.

3.10.4 Step 3: Apply the OEE score to the SAS code for calculating results

The 90% OEE score is coded into SAS which executes the program and is able to provide output regarding the efficiency of the machine. The significance of the OEE score is that after executing each customer order, a result of "Yes" or "No" will be generated by the SAS code. A result of "No" indicates that the machine should perform the task as the OEE is above 90% as opposed to a result of "Yes" which indicates human intervention is needed when the OEE falls below 90%.

3.10.5 Step 4: Input Customer Orders

Several customer orders received via the online Web application, as discussed in Section 3.5, are used as input to SAS. All combinations and permutations of the constraints as well as the OEE score, are taken into consideration resulting in output data that will be used in determining the TTM's for both the machine only approach and the human intervention approach.

3.10.6 Step 5: Calculate the TTM for the Automated approach

The set of customer orders received are used as input to SAS and the TTM for the fully automated approach are calculated.

During the production process, different constraints will be encountered as presented in Table 3.3. The automated plant is preprogrammed, as explained in Section 3.3, to create alerts when these constraints are met after which the automated process reacts accordingly.

An alert is created when the water level or bottles in storage or the caps available reaches 50%, which results in the system to pause or slow down production. The same scenario happens when the levels reaches 25% which makes the system come to a halt while waiting for levels to be replenished and production can resume.

A large number of combinations are possible when taking the constraints into consideration for collecting of the data. See Appendix A for a snapshot from the SAS code for the programming executed to determine the different combinations available. SAS is able to receive the input from customer orders and executes a program to determine the TTM when all the different combinations are taken into account for a specific order. Different scenarios for customer orders will be executed to determine the effect on the automated process. For example, the water level may reach 50% and the bottles available is 25% and caps available is 25%. These combinations have to be programmed into the SAS program for it to determine the effect on the production time for that specific case. The results and findings will be showcased in Chapter 4 indicating the TTM for the fully automated mode without any human intervention.

3.10.7 Step 6: Calculate the TTM for the Collaborative approach

The second part of the experiment, which is the test case, will determine the TTM when human intervention, using HMI's, are introduced to the production process. This is Step 6 of developing the protocol as described in Section 3.3.2. Important to note is that the exact same set of customer orders used in the automated approach will also be used in determining the TTM for the collaborative approach. The results obtained from the execution of the SAS code, will be analyzed and used to compare the TTM for the fully automated mode set against the TTM in the collaborative decision-making mode.

The first step in the Human-Machine collaboration approach, which is the same as with the automated process described in Section 3.10.2, was to determine the average time to fill one 330ml bottle and one 500ml bottle. This process is indicated in Figure 3.10.

After executing the same amount of tests as with the automated approach, it was determined that the average time for filling and capping a 330ml bottle is 45 seconds and 48 seconds for the 500ml, which is identical to the times as established in the automated approach. However, it should be pointed out that these are the average times when all levels are at their optimum stages of 100% for the water, bottles and caps.

For purposes of validating the TTM for a set of orders, a delay is included as mentioned in calculating the TTM with the aim of determining an accurate production time when the mentioned constraints are encountered. These delays occur in the automated approach, seen in Table 3.3, and for execution of the experiments, the same applies to the HMI approach. Therefore a delay of 15 seconds are added in the SAS code to the production time for each 330ml and 500ml bottle when levels reach 50% to allow for a slight delay and 30 seconds when the levels reach 25% while it waits for the levels of bottles or caps to be increased and the water level is replenished.

The next step in the collaborative approach was to introduce the HMI's to SMU1 and SMU2, whereby the human operator will be able to see the status of the different levels of the water, bottles and caps on the interactive HMI screen as the production process continues.

The constraints and variables are indicated in Table 3.2 which show the restrictions or limitations that have to be taken into account in the SAS programming for the different production times or TTM with human intervention. The status of the production process at SMU1 and SMU2 will be clearly visible to the human operator whereby it permits for intelligent decision-making by the human to allow for continuation of the production, slowing down, speeding up or halting the process.

Many different combinations and permutations of the constraints as depicted in Table 3.2, will be encountered during the production process that forms part of the SAS code for determining the TTM when implementing the Human-Machine collaboration approach. The next section will give a more detailed discussion of the programming in SAS used to obtain the results from executing multiple scenarios of the models.

3.11 Applying SAS to the automated and collaborative models

SAS software was used to create datasets from the results obtained after the experiments mentioned in Sections 3.10.1 and 3.10.7 were executed.

As discussed in Section 3.7, the constraints that will be encountered during the production process, should be taken into consideration for determining the TTM of both the Automated approach and the Human-Machine collaboration approach.

For the execution of the data, it is important to note that both fully Automated and Human-Machine collaboration models will use the same set of customer orders for each mode, as mentioned in Section 3.10.5 and 3.10.6. In order to determine the TTM's there are limitations set that will be taken into account when collecting the data, which is the following:

- Total liters of water available = 50lt
- Total no of 330ml bottles = 50
- Total no of 500ml bottles = 50
- Total no of caps = 100 (The same size cap is used for both 300ml and 500ml bottles)

Important to mention is that the automated system has been programmed to sense between the 330ml and 500ml water bottles as per customer order as mentioned in Section 3.4.2.

The variables and variable names used in SAS programming is specified in Table 3.4.

Table 3.4 Variable names and definitions used in SAS.

Variable definition	**Variable name**
Time for machine to complete one bottle	TimeM
Time for HMI to complete one bottle	TimeH
Total liter for 500ml bottle per customer order	TL5
Total liter for 330ml bottle per customer order	TL3
Total liter per customer order	TL
Total number of caps	CapsTot
Total number of 330ml bottles	BotTot3
Total number of 500ml bottles	BotTot5
Total number of 500ml orders	&num
Total number of 330ml orders	&num3
Total time to Manufacture	TTM
Total time to Manufacture Automated mode	TTMA
Total time to Manufacture Human mode	TTMH
Total Time to Manufacture time units	minutes

For the creation of SAS datasets, the TTM per limitation per 500ml and 330ml were used to determine the TTM per customer order. A macro was created to determine the total time and also the amount of liters per set of customer orders.

In order to optimize production, it is imperative to keep track of the amount of water available in the storage tank as well as the number of bottles and caps available.

With reference to Table 3.4, the amount of liters per set of customer orders were calculated as: $TL5 + TL3 = TL$

The same method was used to calculate the amount of total caps and bottles per set of customer orders.

For determining the total time for each customer order, a programming step was created to determine the levels (%) of available water, bottles and caps. This step is necessary to take into account that each limitation has an impact on the time it takes to fill and cap an individual bottle related to both the Automated Mode and the Human-Machine collaboration mode.

The next programming step was to combine TimeM and TimeH per customer order that will indicate the difference in production time for both models.

Finally, the criteria of where human intervention was required to override the automated approach as well as instances where the machine had full control and no human intervention was needed, had to be programmed. The ideal situation, as indicated in Table 3.2 and Table 3.3, are when the constraint levels are all at 100%. As each customer order is being processed, the constraint levels will start decreasing and, as explained previously in Section 3.7.1, an alert will be generated by the automated system, as preprogrammed, when the constraint levels reaches 50% and then again at 25% which causes production to slow down or stop.

The SAS program is coded to provide two outputs depending on the OEE score. If the OEE score of 90% results in an output of "No" the machine can continue when the OEE is above 90% and "Yes" when the OEE is below 90% allowing the human to intervene as explained in Section 3.10.4. The alert is sounded and poses the question to the human operator via the HMI whether the process must stop, continue or slow down. The human can see on the HMI screen the amount of water, bottles and caps left and whether it will be sufficient to complete the order. The human can thus override the machine and indicate that the process can continue.

3.12 Chapter Conclusion

Chapter 3 provided an overview of the research design and methodology involved in the study and the procedures that were followed. The steps for developing a generic protocol for collaborative decision-making were highlighted and applied to the case study of the water bottling plant exploited in this research. The importance of determining an OEE score for measuring machine efficiency was discussed along with the formulas and parameters used to calculate the OEE score to be used in the generic protocol. In the next chapter, Chapter 4, the presentation, analysis and the discussion of the relevant data outputs obtained from the experiments will be discussed. Different scenarios for customer orders will be introduced with the results and findings showcased for each scenario. The aim is to show the automated approach without human intervention and then the results of the model when Human-Machine collaboration is introduced. The TTM for each scenario will be shown for purposes of assessing the results found for the machine only approach as opposed to the Human-Machine collaboration approach of executing the production process of the plant. The results will specify where the machine continues production without human intervention and where human intervention becomes necessary.

Chapter 4: Results and Data Analysis

4.1 Introduction

The aim of this chapter is to showcase the results of the tests that were done on the model as described in Chapter 3. Chapter 4 focusses on the results obtained after executing the experiments and Chapter 5 will be a dicussion of the results. With reference to Chapter 3, a protocol for collaborative decision-making is developed. Sections 3.5 and 3.6 discussed the case study of an existing automated water bottling plant that is used for this study. This chapter will look at how the protocol was implemented using the case study of the automated water bottling plant.

The chapter is structured such that for each scenario, the results for the fully automated approach of the plant will be shared. Secondly the experimental setup and results of the Human-Machine collaborative approach will be highlighted. Finally, an analysis will be done where the two sets of results will be compared to determine which process contributes to the optimization of the production process and where the best fit will be for the human to intervene in an automated production process.

4.2 Customized Testing and Results

The automated model of the plant was discussed in Section 3.7, followed by the execution for the machine that completes the production process without human intervention as explained in Section 3.10.1. The aim of these experiments was to determine the Total Time to Manufacture (TTM) multiple customer orders by taking several constraints and limitations into account and complete the task of filling and capping 330ml and 500ml bottles. Table 3.3 indicates these constraints and limitations. It is important to mention that the experiments were executed in real time utilizing the existing automated water bottling plant.

The Human-Machine collaboration model of the plant was discussed in Section 3.8, after which the Human-Machine collaborative approach to be executed as the test case for the experimental setup was explained in Section 3.8.3. In order to bring the human into the control loop, HMI's were introduced to SMU1 and SMU 2 as discussed in Section 3.8.2.

The output from the SAS program will give the human operator information on when the machine should carry on or whether the human should intervene as described in Section 3.11 by implementing the 90% OEE score for this study. As per discussions in Section 3.3.4, the benchmark OEE for this specific study is 90% while also taking the constraints, as indicated in Table 3.1 and Table 3.2, into consideration. By using the SAS output which applies the OEE to the protocol, as discussed in Section 3.10.4, the protocol will show a "No" when the machine should continue and the HMI is not needed or a "Yes" when the human should intervene. The protocol consequently shows the best way to accomplish a specific task, whether it is the machine or a collaboration between the human and machine. The HMI dictates what should happen when the results show a "Yes", meaning the human can make an informed decision on the production process. The HMI options available to the human once human intervention is flagged by the protocol includes stopping of the process, slowing down or continuing as specified in Table 3.2.

The following section will look at six scenarios for six different customer orders that were executed in fully automated mode, followed by introducing human intervention where after the comparison of machine only and Human-Machine collaboration will be showcased for each scenario. The OEE for this specific case study was set at 90% as stated in Section 3.10.4, hence in all scenarios being presented in the results section where the OEE falls below 90% it was decided that the human should intervene in the production process.

For explaining purposes it was decided to consider the constraints separately as this is the most convenient for the water bottling case study. However, the SAS program is able to look at a number of constraints with *n* number of permutations and combinations. The results are being split into two sections where Scenarios 1 – 3 will initially look at a situation where the water levels are taken as a constraint. Sections 4.6.1 – 4.6.3 shows the results for Scenario 4 – 6 where the bottles and caps are taken as constraints.

The formula for determining the OEE score applied to the SAS code will be implemented for each scenario. The definitions, as described in Section 3.3.1, will be applicable to the calculations.

4.3 Water level as constraint: Scenarios 1 – 3

Customer orders are received via an online web application, as described in Section 3.6, where orders are placed for the filling of 330ml and/or 500ml bottles. Table 4.1 indicates a customer order along with their requirements which were received as input to the SAS program where the manufacturing times of the 330ml and 500ml bottles are calculated as explained in Section 3.11.

Table 4.1 Customer requirements table – Scenario 1

Customer	No of 330ml bottles	No of 500ml bottles	Total No of bottles
A	9	9	18
B	5	4	9
C	6	7	13
D	3	5	8
E	4	2	6
TOTAL NO OF BOTTLES	27	27	54

4.3.1 Scenario 1 – Filling of 330ml and 500ml bottles: Automated mode

Table 4.2 indicates the manufacturing times for the 330ml and 500ml bottles in Automated mode.

Table 4.2 Time to manufacture customer order for 330ml and 500ml bottles – Scenario 1: Automated

Customer	No of 330ml bottles	No of 500ml bottles	Total No of bottles	Time to manufacture 330ml Automated (minutes)	Time to manufacture 500ml Automated (minutes)
A	9	9	18	6,75	7,2
B	5	4	9	3,75	3,2
C	6	7	13	4,5	5,6
D	3	5	8	2,25	5,25
E	4	2	6	5	2,6
TOTAL	27	27	54	22,25	23,85

Figure 4.1 depicts the results for manufacturing the 330ml and 500ml bottles in Automated mode.

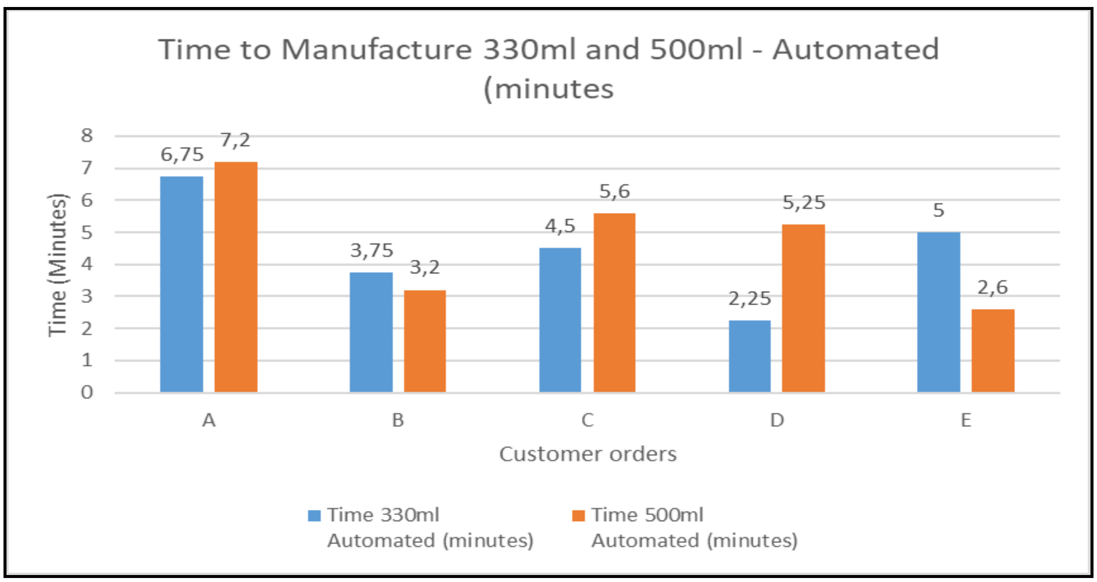


Figure 4.1 Time for manufacturing customer orders for 330ml and 500ml bottles - Automated mode

The following sections will demonstrate the results for Scenario 1 with human intervention introduced to the production process of the plant.

4.3.2 Scenario 1 – Human-Machine Collaboration mode (HMI mode)

Table 4.3 shows the same customer order as in Table 4.1, as the same test data have to be used to execute machine vs. Human-Machine collaboration in order to compare the results of the experiments. The following set of tables and graphs will indicate the results acquired when human intervention was introduced to the production process.

Table 4.3 Customer requirements table – Scenario 1

Customer	No of 330ml bottles	No of 500ml bottles	Total No of bottles
A	9	9	18
B	5	4	9
C	6	7	13
D	3	5	8
E	4	2	6
TOTAL NO OF BOTTLES	27	27	54

4.3.3 Scenario 1 – Filling 330ml and 500ml bottles: HMI mode

Table 4.4 below indicates the manufacturing times for the 330ml and 500ml bottles in human intervention mode.

Table 4.4 Manufacturing time of 330ml and 500ml bottles with human intervention – Scenario 1

Customer	No of 330ml bottles	No of 500ml bottles	Total No of bottles	Time to manufacture 330ml Human Intervention (minutes)	Time to manufacture 500ml Human Intervention (minutes)
A	9	9	18	6,75	7,2
B	5	4	9	3,75	3,2
C	6	7	13	4,5	5,6
D	3	5	8	2,25	4,83
E	4	2	6	3,67	2,27
TOTAL	27	27	54	20,29	23,1

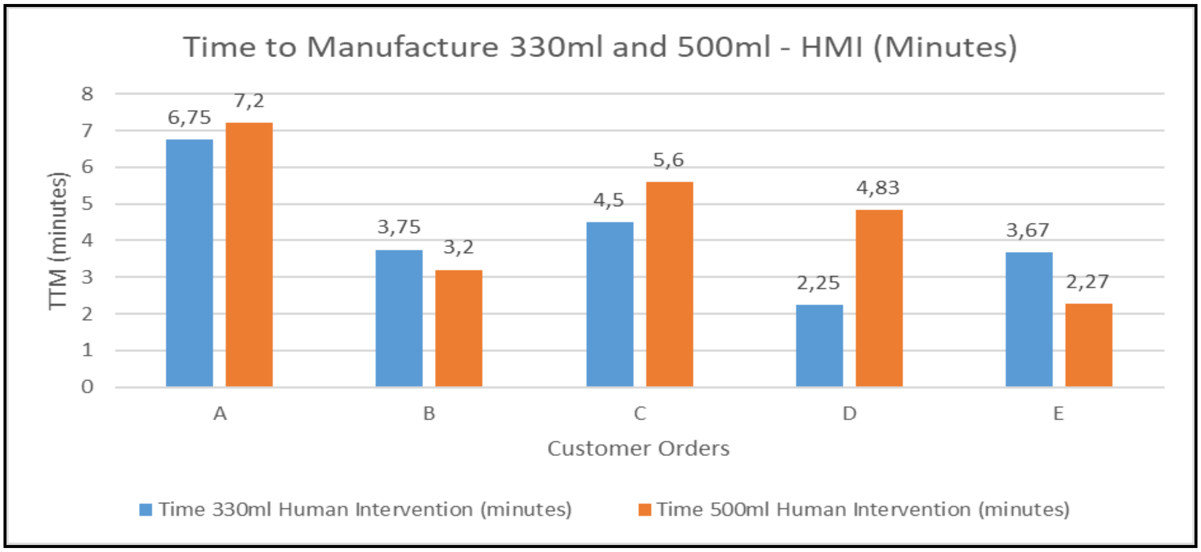


Figure 4.2 Time for manufacturing customer orders of 330ml and 500ml bottles with human intervention

Figure 4.2 portrays the production time for both the 330ml and the 500ml bottles for Scenario 1 in the HMI mode where the human is able to intervene in the production process.

4.3.4 Scenario 1 - Results of the Automated mode vs the Human-Machine Collaboration mode

Table 4.5 shows the results of Scenario 1 where the TTM for the Automated process and the TTM for Human Intervention are presented. As per discussion in Section 3.3.1, the OEE score had to be determined for applying it to the SAS code. Based on the discussions in Section 3.10.3 the benchmark for the OEE used in this study will be at 90%. The rationale behind this, as discussed in Section 3.10.4, is that the OEE score directs whether the machine should continue the production process or whether the human should intervene in the production process. Table 4.5 specifies the OEE percentage and a “Yes” or “No” decision. Depending on the OEE score, a “No” will indicate that the machine can continue the process without human intervention as the OEE is above 90% and a result of “Yes” implies that the human should intervene and override the automated process when the OEE falls below 90% as deliberated in Section 4.2.

For the calculation of the OEE score that was applied to the SAS code, Equation 1 and the following values from Scenario 1 were used to determine the OEE:

(Good Count x Ideal Cycle Time) / Planned Production Time = OEE

Good Count = Total no 330ml + 500ml bottles for customer order

= 54 bottles

Ideal Cycle Time = Average time of producing a 330ml + a 500ml bottle per cycle

= (48 seconds x 45 seconds)

= 93 seconds / 2

= 0,775 seconds

Planned Production Time = Total Time to Manufacture customer order

= 46,1 minutes

(Good Count x Ideal Cycle Time) / Planned Production Time = OEE

(54 x 0.775min)/46,1 = 90,7%

Table 4.5 TTM of Automated mode vs HMI mode – Scenario 1

Customer	Total no of Bottles	TTM Automated (minutes)	TTM Human Intervention (minutes)	Total Lt used	OEE %	Human to Intervene
A	18	13,95	13,95	7,47	100%	No
B	9	20,9	20,9	11,12	100%	No
C	13	31	31	16,6	100%	No
D	8	38,5	38,08	20,09	98,91%	No
E	6	46,1	44,02	22,41	95,49%	No
Totals	54	46,1	44,02			

The results of Scenario 1 for Human-Machine collaborative decision-making versus the automated mode, is shown in Figure 4.3. When considering the times to manufacture for this specific scenario, one sees that for Customer order A, B and C it takes the same amount of time to fill and cap the water bottles, after which, as the production process continues, the TTM's starts to fluctuate.

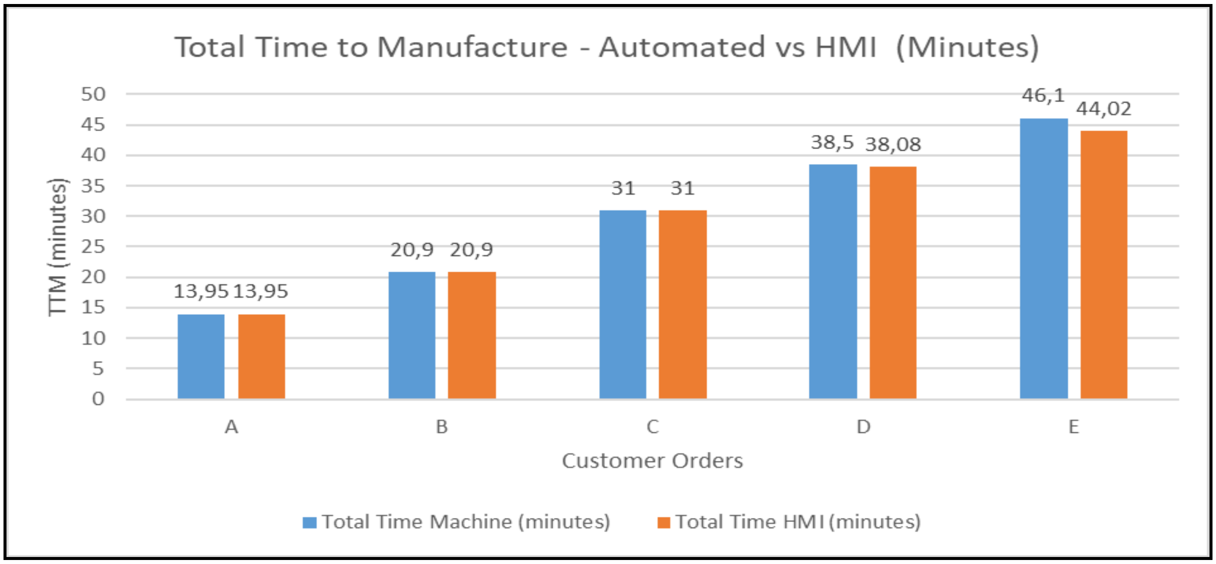


Figure 4.3 Results of the TTM for Automated mode vs HMI mode – Scenario 1

The amount of water used to complete the customer order is indicated in Table 4.5 which amounts to 22 liters. In this scenario, the water level is just above 50% on completion of the order. As stated in Table 3.3, the machine is pre-programmed to pause when the water level reaches 50% and when at 25% comes to a halt while it waits for the water level to be replenished. However, there is still enough water available and thus the plant is able to complete the customer order without human intervention.

Figure 4.3 depicts the combined TTM's for Scenario 1 in the Automated as well as the Human Intervention mode. Table 4.5 indicates the efficiency percentage of the plant by applying the OEE score as discussed in Section 3.10.4 . The "No" indicates that the machine completes the order without human intervention and "Yes" when human intervention should take place.

4.4 Water level as constraint: Scenario 2

4.4.1 Scenario 2 – Fully Automated Mode

The following tables and graphs for Scenario 2 indicates the manufacturing times for a second customer order and will show the results for the automated mode, the human intervention mode followed by a comparison between the TTM results of the automated vs the human intervention mode.

Table 4.6 Customer requirements table - Scenario 2

Customer	No of 330ml bottles	No of 500ml bottles	Total No of bottles
A	13	15	28
B	8	12	20
C	10	11	21
D	8	7	15
E	10	5	15
TOTAL NO OF BOTTLES	49	50	99

4.4.2 Scenario 2 - Filling the 330ml and 500ml bottles: Automated mode

The customer orders for Scenario 2 of fillling the 330ml and 500ml bottles are shown in Table 4.7 indicating the total times for filling and capping the bottles. The results are depicted as a graph in Figure 4.4.

Table 4.7 Customer orders for 330ml and 500ml bottles with the manufacturing times in automated mode – Scenario 2

Customer	No of 330ml bottles	No of 500ml bottles	Total No of bottles	Time to manufacture 330ml Automated (minutes)	Time to manufacture 500ml Automated (minutes)
A	13	15	28	9,75	12
B	8	12	20	6	12,6
C	10	11	21	12,5	19,8
D	8	7	15	16	14,35
E	10	5	15	22,5	11,5
TOTAL	49	50	99	66,75	70,25

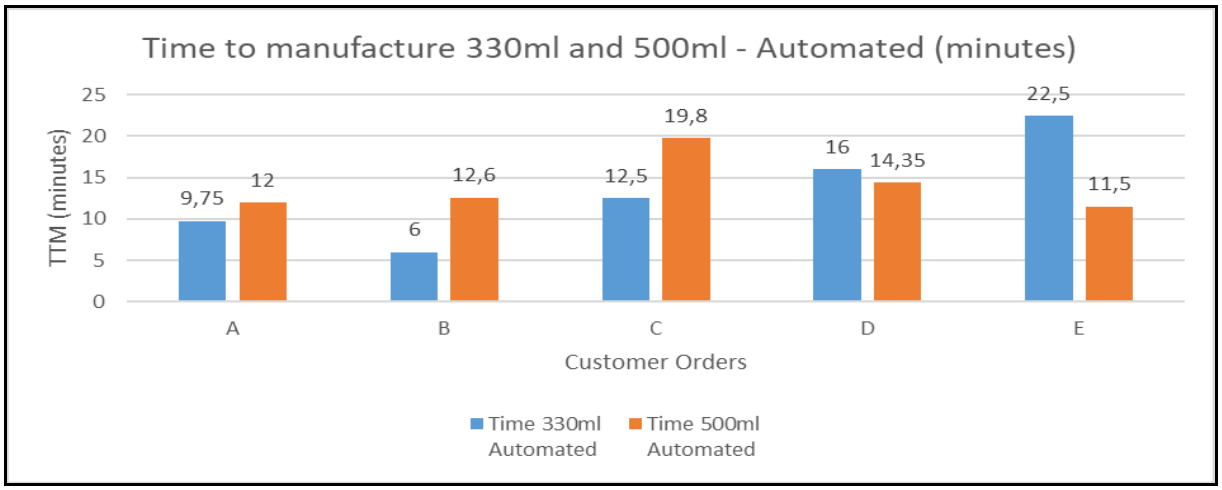


Figure 4.4 Results of filling 330ml and 500ml bottles for Scenario 2: Automated mode

4.4.3 Scenario 2 – Human Intervention mode

For the execution of the customer order for Scenario 2 in HMI mode, the same set of orders as shown in Table 4.6 are used as input to SAS, since the same test data is used to execute machine vs. Human-Machine collaboration for comparing the results of the experiments. The following set of tables and graphs will indicate the results attained when human intervention was introduced to the production process.

4.4.4 Scenario 2 – Filling the 330ml and 500ml bottles in HMI mode

The time to manufacture both the 330ml and 500ml bottles are indicated in Table 4.8 and it perceptible that the manufacturing process takes significantly more time to complete when compared to Scenario 1. This is due to the large customer order received.

Table 4.8 Time to manufacture the 330ml and 500ml bottles in HMI mode - Scenario 2

Customer	No of 330ml bottles	No of 500ml bottles	Total No of bottles	Time 330ml Human Intervention (minutes)	Time 500ml Human Intervention (minutes)
A	13	15	28	9,75	12
B	8	12	20	6	11,6
C	10	11	21	9,17	15,22
D	8	7	15	9,33	10,27
E	10	5	15	12,5	7,75
TOTAL	49	50	99	46,75	56,84

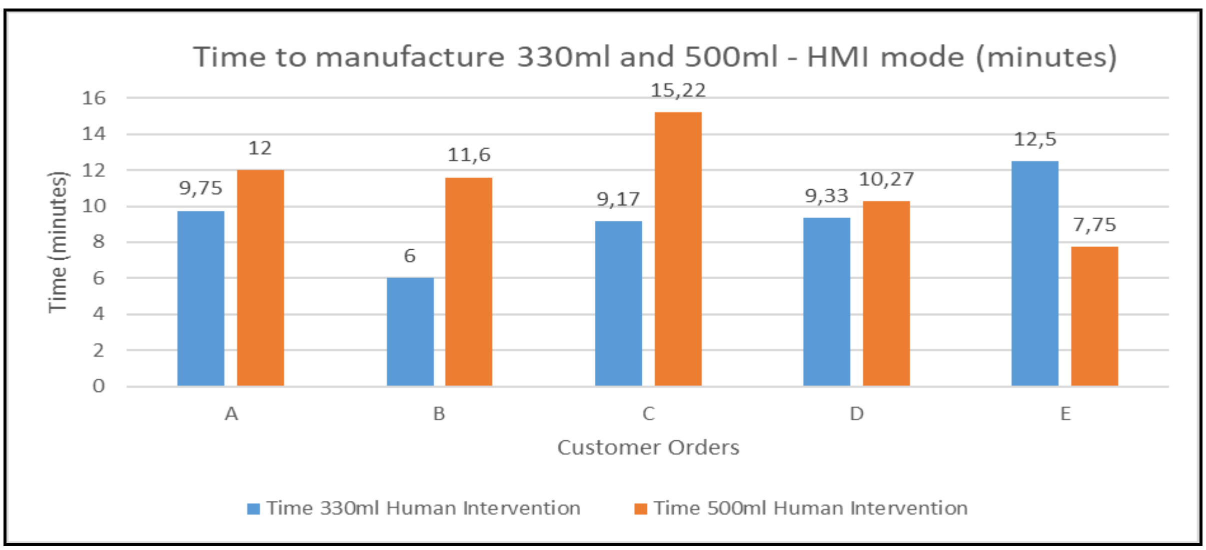


Figure 4.5 Results of applying the HMI mode for filling the 330ml and 500ml bottles – Scenario 2

4.4.5 Scenario 2 – TTM of the customer order: Automated mode vs HMI mode

Table 4.9 shows the TTM's for the Automated process as opposed to the Human Intervention mode. Figure 4.6 portrays the TTM's for both the Automated mode and the Human Intervention mode.

The calculation of the OEE score for Scenario 2 is shown below:

(Good Count x Ideal Cycle Time) / Planned Production Time = OEE

Good Count = Total no 330ml + 500ml bottles for customer order

= 99 bottles

Ideal Cycle Time = Average time of producing a 330ml + a 500ml bottle per cycle

= (48 seconds x 45 seconds)

= 93 seconds / 2

= 0,775 seconds

Planned Production Time = Total Time to Manufacture customer order

= 137 minutes

(Good Count x Ideal Cycle Time) / Planned Production Time = OEE

(99 x 0.775min)/103.59 = 74,06%

Table 4.9 TTM of manufacturing in Automated mode vs HMI mode – Scenario 2.

Customer	Total No of bottles	TTM Automated (minutes)	TTM Human Intervention (minutes)	Total Lt used	OEE %	Human to Intervene
A	28	21,75	21,75	11,79	100%	No
B	20	40,35	39,35	20,43	97,52%	No
C	21	72,65	63,74	29,23	87,74%	Yes
D	15	103	83,34	35,37	80,91%	Yes
E	15	137	103,59	41,17	75,61%	Yes
Total no of bottles	99	137	103,59			

At the completion of the order, the total water used to fill the bottles were approximately 41 litres, which is still below the limitation of 50 litres, although the water level is under 25%. Referring to the OEE percentage exhibited in Table 4.9, it is clear to determine when the machine should continue and when the human operator should intervene in collaboration with the machine for the completion of the order. As one can see in Table 4.9, a total of 137 minutes were used to complete the order in Automated mode in contrast to the HMI mode that used 103 minutes for completion of the order.

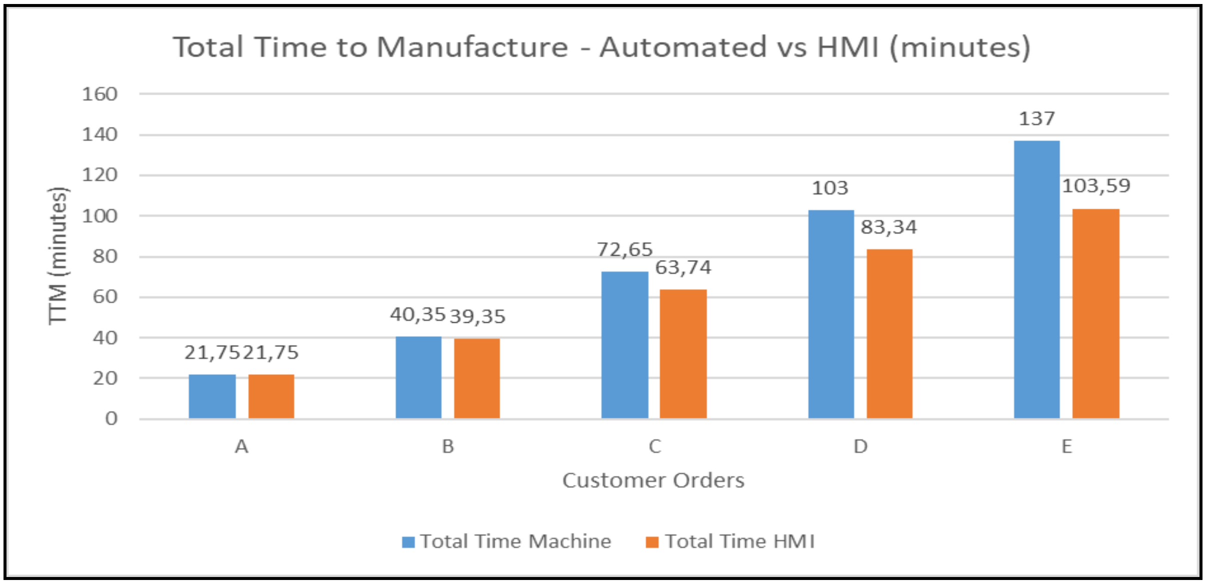


Figure 4.6 Results of the TTM for Automated mode vs HMI mode for completing the customer order – Scenario 2.

4.5 Water level as constraint: Scenario 3

4.5.1 Scenario 3 - Fully Automated mode

The last scenario that showcases the results of the two models with the water level as a constraint is presented in Sections 4.5.2 up to Section 4.5.8.

The following tables and graphs for Scenario 3 indicate the times to manufacture the 330ml and the 500ml bottles for another customer order, Scenario 3, and will show the results for the Automated mode, the HMI mode followed by a comparison between the TTM results of the Automated vs the HMI mode.

Table 4.10 Customer requirements table - Scenario 3.

Customer	No of 330ml bottles	No of 500ml bottles	Total No of Bottles
A	8	26	34
B	8	25	33
C	6	19	25
D	6	13	19
E	3	16	19
TOTAL	31	99	130

For the order in Scenario 3, a total of 130 bottles must be filled as shown in Table 4.10.

4.5.2 Scenario 3 – Filling the 330ml and 500ml bottles: Automated mode

In Table 4.11 it can be seen that the number of 500ml bottles are significantly more than the required 330ml bottles. The manufacturing time for the 330ml bottles are approximately 38 minutes while the time for the 500ml bottles are approximately 183 minutes.

Table 4.11 Time to manufacture 330ml and 500ml bottles – Scenario 3 (Automated)

Customer	No of 330ml bottles	No of 500ml bottles	Total No of Bottles	Time to manufacture 330ml Automated (minutes)	Time to manufacture 500ml Automated (minutes)
A	8	26	34	6	27,3
B	8	25	33	6	45
C	6	19	25	7,5	43,7
D	6	13	19	12	29,9
E	3	16	19	6	36,8
TOTAL	31	99	130	37,5	182,7

The diagram in Figure 4.7 below shows the results for filling applying the Automated mode for the 330ml and 500ml bottles.

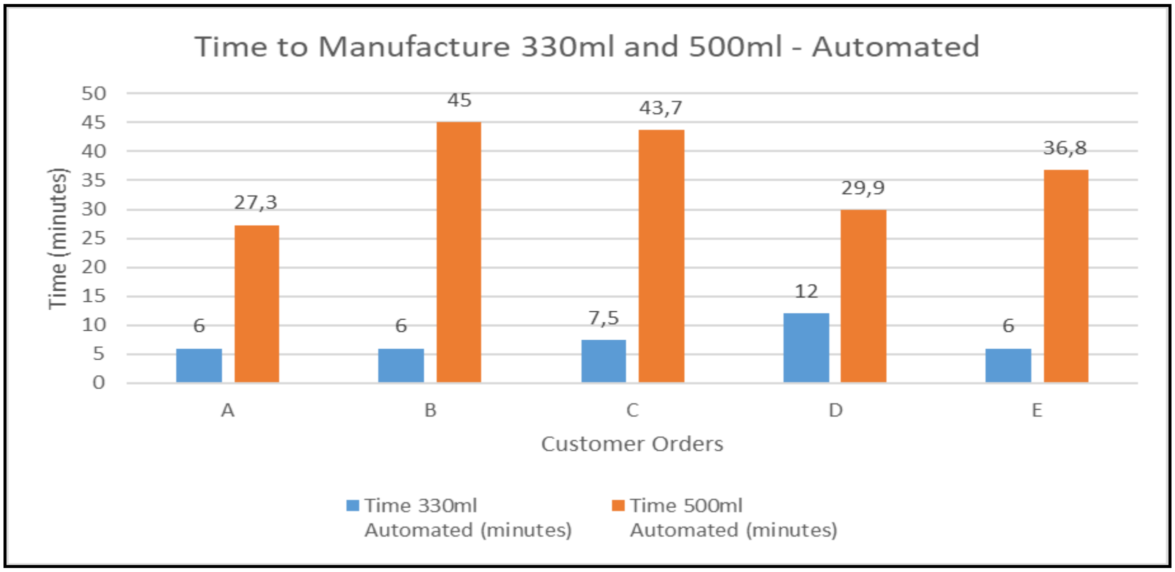


Figure 4.7 Results of the TTM for the Automated mode of filling 330ml and 500ml bottles

4.5.3 Scenario 3 – Filling the 330ml and 500ml bottles: HMI mode

The following table, Table 4.12, indicates the manufacturing times for both the 330ml and the 500ml bottles when implementing the HMI mode.

Table 4.12 Manufacturing time for 330ml and 500ml bottles: HMI mode

Customer	No of 330ml bottles	No of 500ml bottles	Total No of Bottles	Time to manufacture 330ml Human Intervention (minutes)	Time to manufacture 500ml Human Intervention (minutes)
A	8	26	34	6	25,13
B	8	25	33	6	34,58
C	6	19	25	5,5	29,45
D	6	13	19	7	20,15
E	3	16	19	3,5	24,18
TOTAL	31	99	130	28	133,49

In Figure 4.8, one can see that there were considerable more orders for the 500ml bottles which resulted in significantly more time to complete the orders for the 500ml’s.

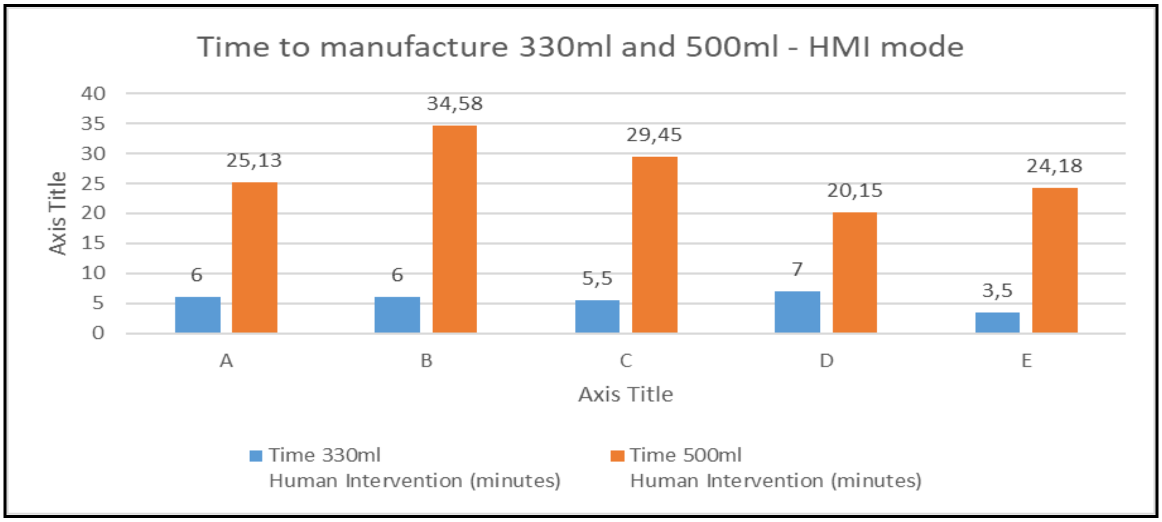


Figure 4.8 Results of the manufacturing times for the HMI mode of filling the 330ml and 500ml bottles - Scenario 3

4.5.4 Scenario 3 – TTM for manufacturing customer order: Automated mode vs HMI mode

Table 4.13 displays the results of the Total Time to Manufacture (TTM) when the automated mode is compared to the HMI mode. In this instance almost 60 liters of water were used to complete the order while the limitation, as specified in Section 3.12, is 50 liters of water. Figure 4.9 demonstrates the TTM results in the chart below.

The OEE score for this scenario is as follows:

(Good Count x Ideal Cycle Time) / Planned Production Time = OEE

Good Count = Total no 330ml + 500ml bottles for customer order

= 130 bottles

Ideal Cycle Time = Average time of producing a 330ml + a 500ml bottle per cycle

= (48 seconds x 45 seconds)

= 93 seconds / 2

= 0,775 seconds

Planned Production Time = Total Time to Manufacture customer order

= 162,11 minutes

(Good Count x Ideal Cycle Time) / Planned Production Time = OEE

(99 x 0.775min)/162,11 = 47,32%

As can be seen in the result of the calculated OEE for this scenario, the OEE score drops to 47% which indicates that the OEE also depends on the order size. The automated system is stochastic in nature, as explained in Section 2.2, which results in several different order sizes. However, the benchmark, as mentioned previously, is 90% for this case study.

Table 4.13 TTM's to manufacture the 330ml and 500ml bottles – Scenario 3 (HMI)

Customer	Total No of Bottles	TTM Automated (minutes)	TTM Human Intervention (minutes)	Total Lt used	OEE %	Human Intervention
A	34	33,3	31,13	15,64	93,48%	No
B	33	84,3	71,71	30,78	85,06%	Yes
C	25	135,5	106,66	42,26	78,71%	Yes
D	19	177,4	133,81	50,74	75,43%	Yes
E	19	220,2	162,11	59,73	73,61%	Yes
Total no of bottles	130					

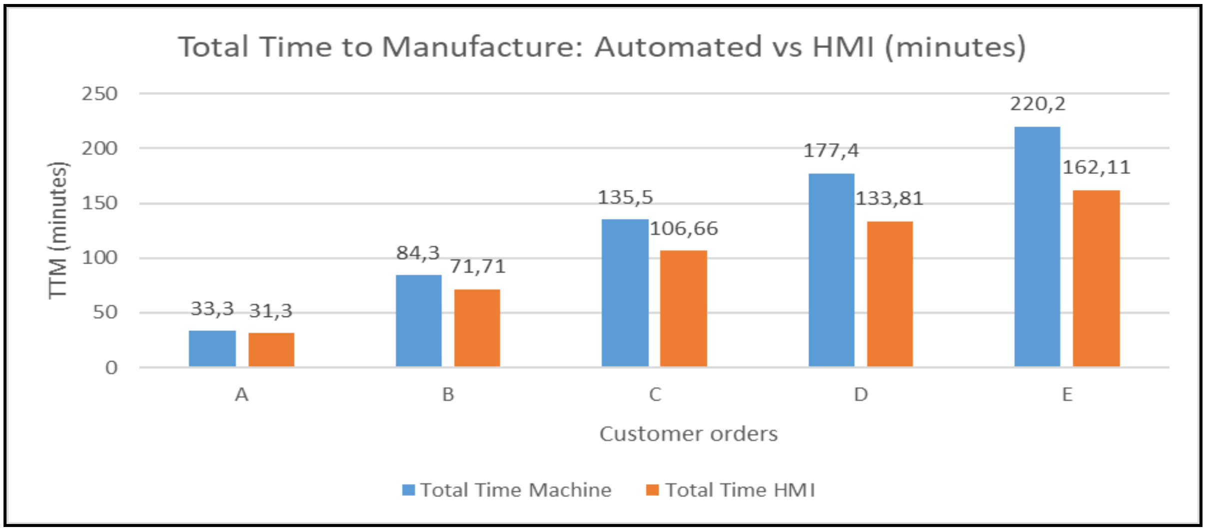


Figure 4.9 Results of the TTM's for the Automated mode vs the HMI mode - Scenario 3.

Based on the findings for Scenario 3, Figure 4.9 shows that this specific order was relatively large as 130 bottles in total needed filling and capping. Therefore the human had to intervene in the process from customer order B as indicated by the OEE score and the TTM for the complete operation was 220,2 minutes for the Automated approach and 162,11 minutes for the Human-Intervention approach.

4.6 Bottles and caps as constraints: Scenarios 4 – 6

The second set of variables, as specified in Section 3.8, namely the number of bottles and caps, were used as input to the SAS program for establishing the TTM for three different sets of customer orders. The same constraints as with the water level apply to the water bottles and caps as they all are variables used to program the SAS code. Scenarios 4 – 6 have very similar results as that of Scenario 1 – 3 and based on the bottles and caps as constraints. For this reason, only the comparison of the Automated approach as opposed to Human-Machine collaboration approach will be showcased for each scenario. The full set of results are available in Appendix B.

4.6.1 Scenario 4 - TTM for manufacturing in Automated mode vs HMI mode

Table 4.14 TTM for filling and capping: Automated vs HMI – Scenario 4 (HMI)

Customer	Total No of Caps & Bottles	TTM Automated (minutes)	TTM Human Intervention (minutes)	Total Lt used	OEE %	Human Intervention
A	10	7,6	7,6	3,64	100%	No
B	11	16,3	16,3	8,8	100%	No
C	5	20,2	20,2	10,96	100%	No
D	4	23,25	23,25	12,45	100%	No
E	9	30,2	30,2	16,1	100%	No
TOTAL	39	30,2	30,2			

Based on the results in Table 4.14, the Automated system completed the order without any human intervention.

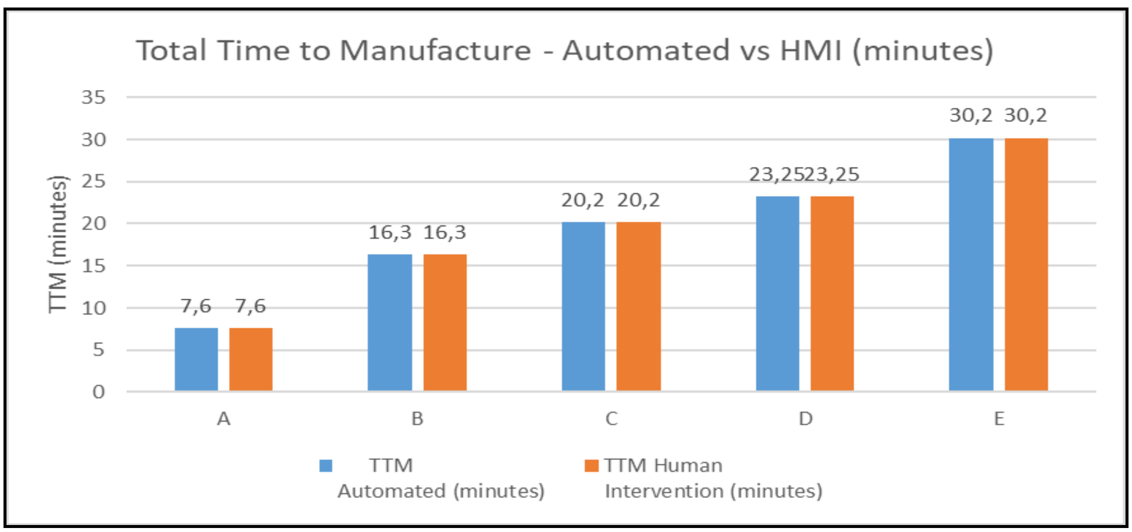


Figure 4.10 TTM for filling and capping: Automated mode vs HMI mode - Scenario 4.

As can be seen from the results showcased in Figure 4.10 the TTM for both modes were the same for this scenario. The total amount of water used for filling and capping the 39 bottles for this customer order were 16 liters. The constraints never reached 50% which means that the machine could complete the order without human intervention.

4.6.2 Scenario 5 - TTM for manufacturing 300ml and 500ml bottles: Automated mode vs HMI mode

Table 4.15 TTM of customer order for the 330ml and 500ml bottles: Automated vs HMI mode – Scenario 5.

Customer	Total no of caps and bottles	TTM Automated (minutes)	TTM Human Intervention (minutes)	Total Lt used	OEE%	Human Intervention
A	13	21,75	21,75	11,79	100%	No
B	31	55,35	50,35	23,73	90,97%	No
C	38	90,15	74,06	31,54	82,15%	Yes
D	41	110,5	87,83	36,03	79,48%	Yes
E	45	130	100,25	39,85	77,11%	Yes
TOTAL	95	130	100,25			

For this specific order, the total amount of liters used to fill and cap the 330ml and 500ml bottles were almost 40 liters. The number of bottles and caps needed were 95 as seen in Table 4.15. The results, according to the OEE score, gives an indication of where the human should intervene in the production process. The TTM for completing this order in Automated and Human Intervention mode is displayed in Figure 4.11.

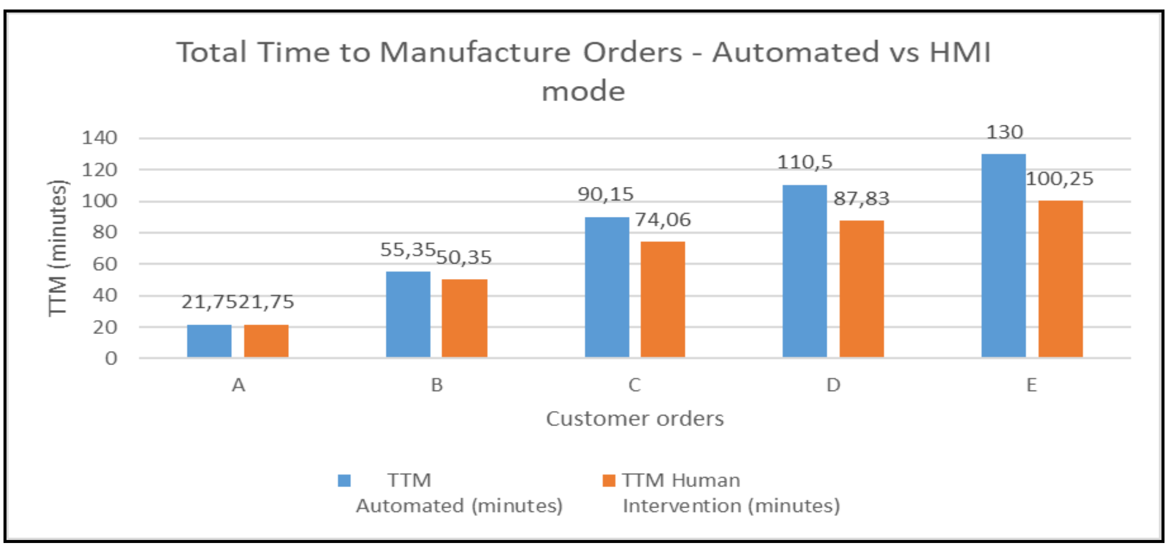


Figure 4.11 Diagram showing the TTM of filling and capping all customer orders for 330ml and 500ml bottles: Automated vs HMI mode - Scenario 5.

4.6.3 Scenario 6 - TTM for filling and capping customer order: Automated vs HMI mode

The results, according to the OEE score in Table 4.16, gives an indication of where the human should intervene in the production process. For this specific order, the total amount of liters used to fill and cap the 330ml and 500ml bottles were almost 42 liters. The number of bottles and caps needed were 102 as seen in Table 4.16. The TTM for completing this order in Automated and Human Intervention mode is displayed in Figure 4.12.

Table 4.16 TTM of customer order for the 330ml and 500ml bottles: Automated vs HMI mode – Scenario 6

Customer	Total No of Caps & Bottles	TTM Automated (minutes)	TTM Human Intervention (minutes)	Total Lt used	OEE%	Human Intervention
A	21	16,2	16,2	8,46	100%	No
B	26	40,5	39,17	19,76	96,71%	No
C	28	90	73,83	30,7	80,56%	Yes
D	12	114,25	105,5	35,51	77,02%	Yes
E	15	148,4	135,4	41,82	73,55%	Yes
TOTAL	102	148,4	135,4			

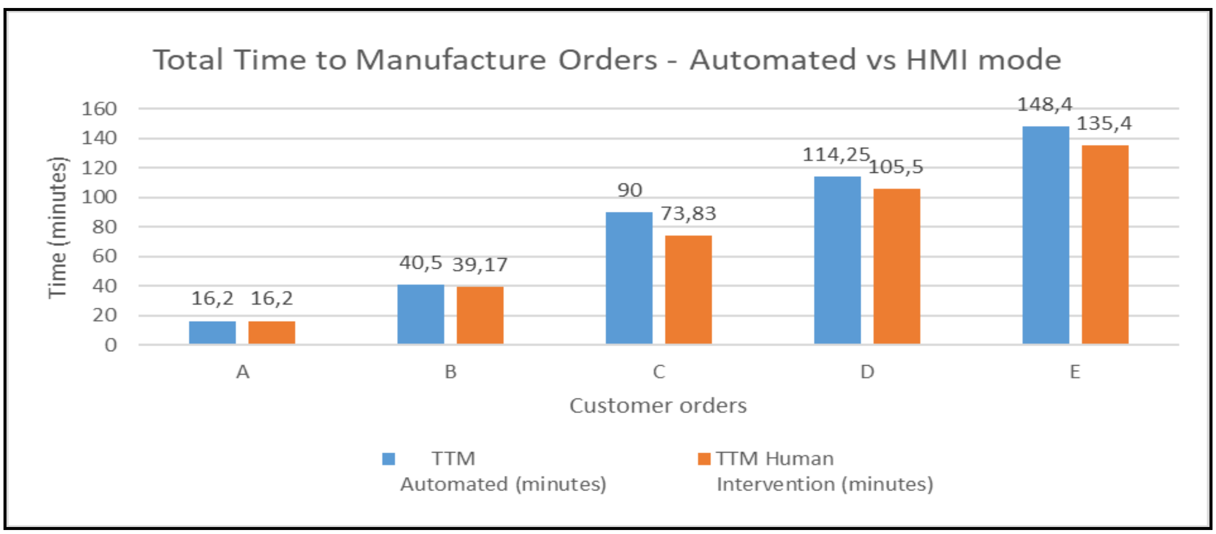


Figure 4.12 Diagram showing the TTM of filling and capping all customer orders for 330ml and 500ml bottles: Automated vs HMI mode - Scenario 6.

4.7 Chapter Conclusion

The focus of this chapter was on presenting the results that was acquired by executing the SAS program, as explained in Section 3.12, when multiple tests with different variables were used as input to the program. The aim was firstly to showcase the results obtained for performing orders of the fully Automated approach of the plant for a set of customer orders. Secondly, the results for the execution of the Human-Machine collaborative approach using the same set of customer orders were highlighted. Lastly, a comparison between the results of the Automated approach was compared to the Human-Machine collaboration results found during the execution of multiple experiments on a set of customer orders.

By applying the OEE score to the SAS code, it was determined that an OEE score above 90% indicates that the machine should continue the production process without human intervention but as soon as the OEE is below 90%, the human should intervene in the process by overriding the automated system.

According to literature, an OEE score of 85% is world class [58] to implement although the value can change. The generic protocol allows businesses or companies for the adaptation and deciding on their own parameter for the relevant OEE score. Appendix D showcases the results if an OEE score of 85% is implemented for executing the experiment on the same set of customer orders used for this study.

Chapter 5 will focus on a detailed discussion of the results and findings of the execution of the experimental setup to establish which process contributes to production optimization and where the best fit will be for human intervention in the automated production process.

CHAPTER 5: Discussion

5.1 Introduction

The following chapter discusses how the research gap, identified through the limitations of existing research discussed in Section 2.5, have been negated through this study. In doing so, the chapter aims to present the original contribution of the study. This is accomplished by reviewing the results for each scenario and elaborating on the insights gained from the analyzed data.

5.2 Summary of limitations

The limitations of the existing research, point to the fact that a close collaboration between humans and machines are of vital importance in the manufacturing environment. However, a conclusion was reached that there exists a lack of a protocol or guidelines for deciding when a machine or a collaboration between the human and machine, should undertake a specific task in an automated environment.

The aim of this research is to investigate and establish the importance of human intervention in a collaborative decision-making process for the optimum completion of tasks performed by an ICT enabled Smart automated manufacturing system and propose a protocol to determine the tasks/actions best performed by machine, by a human and a collaboration of human and machine. Although a level of human involvement is very visible in the examples discussed in Section 2.5, a common thread is that there are no usable guidelines for the distribution of tasks or actions between humans and machines.

Based on the discussion in the literature review, specifically with reference to Section 2.2, it was highlighted that Industry 4.0 is set to revolutionize the way manufacturing has been done thus far [11]. Traditionally, industries made use of a make-to-stock approach which signified that products were manufactured to be stocked up ahead of customer demand. In the Industry 4.0 era, the focus of manufacturing industries have shifted towards a make-to-order approach which is geared towards the individual needs from customers.

The problem with the make-to-stock approach is that the demand for products are stochastic which implies that it cannot be predicted precisely what the customer requirements will be and the factory has to depend on a random probability for manufacturing of products.

The nature of this study is to make use of a mixed-model stochastic approach whereby the customers are able to place orders based on their specific make-to-order needs. The inputs received from the Web based ordering system for this case study were all random amounts of orders that needed completion by the automated water bottling plant as presented in Chapter 4 of the results section.

Based upon the limitations of existing research, an approach using a single-case experimental study was implemented to execute multiple experiments. Section 3.2.1 gave a description of a single-case experiment whilst Section 3.2.2 indicated the motivation of using a single-case experiment as well as the goal of the experimental case study. The approach followed for the execution of the single-case experiment were discussed in Section 3.2.3. The development of a generic protocol was deliberated in Section 3.3 as well as the steps to follow for developing a generic protocol which includes the definition, importance and determining of the Overall Equipment Effectiveness (OEE) score needed in creating the protocol.

The ensuing sections included a detailed reflection on the execution of the experiments on the automated mode versus the human-collaboration mode by using SAS programming. The results of the experiments were shared in Chapter 4. The aim of the experiments were to determine the Total Time to Manufacture (TTM) a specific set of customer orders. The same set of orders were tested for machine only followed by testing a collaboration between human and machine, which delivered results for the manufacturing time for each approach. By comparing the results of the two models based on the output from SAS, conclusions can be drawn that assists in developing a set of guidelines to indicate when a Human-Machine collaboration should be used during the production process.

5.2.1 Scenario 1 discussion

The customer requirements for the first customer order is represented in Table 4.1 where it is specified that the total number or bottles to be filled and capped for Scenario 1, is 54 bottles, including all the 330ml and 500ml bottles for the specific order. The TTM's for both the Automated approach and the Human-Machine collaboration approach was determined and the results of these experiments are illustrated in Figure 4.3.

Based on the results of Scenario 1, Table 4.5 shows the TTM's for both automated and human intervention and also the total amount of water used for completing the customer order. The OEE percentage in Table 4.5 signifies whether the machine should continue the production process without human intervention or when the human should intervene. These decisions are based on the OEE percentage where an OEE above 90% results in a "No" indicating the machine should continue or a "Yes" when the human should intercede, as discussed in Section 3.10.4.

Figure 4.3 reveals that the TTM's for both approaches producing customer order A takes exactly the same amount of time, which is 13,95 minutes. The rationale for these results are that at the beginning of the production cycle all levels of water, bottles and caps start at 100%. As a consequence of these levels, both approaches will use the same time to complete the order.

The TTM for Customer order B is also the same for both approaches, which is 20,9 minutes. In this instant the water level is still above 50% of the 50 liter limit, thus the machine can continue production without human intervention as is observable in Table 4.5. The same applies for Customer order C where it can be seen in Figure 4.3, that the automated mode takes slightly longer than the human intervention mode. However, the amount of water used at this point in time is still above 50% thus the automated process will continue without any human intervention.

Although an alert will be generated when the water level reaches 50% and then again at 25%, as explained in Section 3.7.1, the process can continue in automated mode as the constraints are within an acceptable range for completing the order and the OEE score is above 90%. Figure 4.3 illustrates the TTM's for the Automated approach vs. the Human Intervention approach. Owing to the fact that the amount of water, bottles, caps and the OEE are taken into consideration during the execution of the experiment, the entire customer order in Scenario 1 was executed in the Automated mode. On further testing, the reason for this was that there was adequate water, bottles and caps available, and/or the number of orders were less than the constraints as outlined in Section 3.10.2.

5.2.2 Scenario 2 discussion

The customer order for Scenario 2 consisted of 99 bottles that needed filling and capping as seen in Table 4.9. Based on the results of the second scenario, illustrated in Figure 4.6, it is detectable that there are more instances where the human needs to intervene. Table 4.9 summarizes the TTM's for both approaches where it shows that the total amount of water used for this particular customer order was 41 liters, which is very close to the limit of 50 liters.

The graphical representation in Figure 4.6 shows the difference in production time for the Automated mode and the Human-Intervention mode. The total time for the Automated process is 137 minutes, and for the Human-Intervention mode the time to manufacture is 104 minutes. Furthermore, Table 4.9 exhibits that at least 60% of the task requires human intervention and this is as a result of the amount of water used for the production process.

According to the OEE results in Table 4.9, human intervention is needed starting from the order for Customer C as the water reaches a level below 50% which causes an alert to be generated by the system, as presented in Table 3.1, when the process will come to a pause. At this juncture, the human will be able to make a decision given the information received from the SAS code and viewing the overall status of the system on the SCADA.

The human can perceive the data indicating that there are still a number of bottles that needs filling, but it is evident that there is still enough water in the tank for completing the order, thus allows the human to intervene and override the automated process and continue production. This particular scenario demonstrates a well-balanced task allocation between the human and the machine.

5.2.3 Scenario 3 discussion

A classic example of a scenario where the human needs to intervene more actively, can be seen in Scenario 3 where Figure 4.9 shows the results of the TTM's for the Automated mode vs the Human-Intervention mode. Table 4.13 indicates the total number of bottles to be filled and capped for this scenario which amounts to 130 bottles. This specific customer order requires more bottles, caps and water as per the limits available specified in Section 3.11.

From the results in Figure 4.6 it is obvious that after completing Customer A's order, the TTM for human intervention is less than for the automated approach. Up to this point the automated modes takes 33,3 minutes as opposed to the HMI approach which takes 31,13 minutes. An amount of 15,64 liters were used to complete the order for Customer A allowing the machine to carry on and complete the order as the water level is well above 50% and the OEE percentage is above 90%.

When Customer order B is processed, Table 4.13 shows that the amount of water used reached a level of 30,78 liters, which is below the 50% water level and thus an alert is generated while the process pauses as preprogrammed and the question whether to proceed or not is posed to the human operator. At this point the OEE percentage is below the 90% benchmark and the results indicate that the human should intervene by overriding the automated process.

The SCADA and HMI allows the human to estimate that there is enough water in storage to complete the order and the human can make a decision in advance for the obtaining of more bottles and caps. These scenarios point out that human intervention plays a critical role in making informed decisions based on the information received.

The same results are seen for Customer orders D and E where the OEE is below 90% and the amount of water used is below the limits set and therefore needs the human to intervene and work in collaboration with the machine for completing the orders, thus contributing to a faster completion time of the customer order

The following sections will discuss Scenarios 4 – 6 where the bottles and caps were used as the constraints.

5.2.4 Scenario 4 discussion

The same constraints as with the water level apply to the water bottles and caps as they are all used as variables to program the SAS code.

Table 4.14 specifies the customer requirements for the order in Scenario 4, which consists of a total number of 39 bottles and caps. The time to manufacture the customer order is determined by executing the SAS code and indicates the amount of water, bottles and caps used to complete the order. Table 4.14 shows the TTM for both the Automated and HMI approach and is depicted in Figure 4.10 where it is noticeable that the TTM for both approaches were the same, which is 30,2 minutes. The amount of water used to complete the order was 16 liters which is well above the 50% level of the storage tank and 39 bottles and caps were used which is below the limits as set out in Section 3.11.

The results obtained from the SAS program indicates that the OEE percentage is well above 90% and the constraint levels never reached 50% which allowed the machine to complete the order in fully automated mode without any human intervention needed.

5.2.5 Scenario 5 discussion

The customer requirements for Scenario 5 are indicated in Table 4.15 which shows a total number of 95 bottles for the 330ml and 500ml to be filled and capped. Table 4.15 shows the results of the TTM for Automated mode versus the HMI mode after execution of the SAS program.

Both Customer orders A and B were executed by the machine only as the constraint levels are above 50% and the OEE is above 90%. As soon as the constraint levels reach 50% or 25%, the alert is sounded where the HMI requests whether production should continue, slow down or stop. This is the case where Customer order C, D and E is encountered where the constraint levels drops below 50%. When Customer order C is reached, the amount of bottles and caps are 38 which is below the 50% level. At this instant the human can determine whether there is enough water, bottles and caps available for the process to continue or stop, by making use of the information received and displayed on the HMI.

The same applies to Customer orders D and E. For completion of the order, almost 40 liters were used but human intervention was needed when the limitations of the constraints were met. Figure 4.11 shows the chart with the resulting output of Scenario 5 indicating the TTM's for the Automated Mode in contrast to the HMI Mode. The TTM for the HMI Mode took 100,25 minutes to complete as opposed to the automated process that took 130 minutes to complete the order of the 95 water bottles. Based on the results, the collaboration between the human and machine was the approach that resulted in the optimization of the production process.

5.2.6 Scenario 6 discussion

Scenario 6 is the final example that is presented for this particular study. The requirements of the customers are indicated in Table 4.16 where it displays that a total number of 102 bottles are required to be filled of which 54 was 330ml bottles and 48 bottles for the 500ml's. After executing the SAS program, the results for both the Automated and HMI approaches were presented. The results obtained after executing the SAS program is presented in Table 4.16. For the filling and capping of the 102 bottles, the total amount of water used was almost 42 liters, which is very close to the limit of 50 liters.

The TTM for the Automated approach was 148 minutes and the HMI approach needed 135,4 minutes to complete the order. As can be seen in Table 4.16, customer orders A and B were completed without any human intervention as the level of 50% was not reached when producing these orders.

When the order for Customer C is reached, the amount of water is at 30,7 liters which is below the 50% level and the OEE is below 90%. The results indicate that the human is required to make a decision to complete the order or to slow it down or stop while levels are replenished. However, the human can see that there is still enough water, bottles and caps available and therefore overrides the machine to continue production and complete the order. Figure 4.12 illustrates the output of the test performed for completing the customer order for Scenario 6. The results obtained for Scenario 6 established that the Human-Machine collaboration approach was faster than the Automated Mode and therefore assists in an optimum production time for the process.

5.3 Protocol for Collaborative Decision-Making

The limitations of existing research were highlighted in Section 2.5 where it was indicated that, at the time of writing this thesis, there were no usable guidelines or protocols to assist in making informed decisions of how the task allocation should be distributed between humans and machines.

Work done by Kruger, et.al [68], Ponsa, et.al [21], Muller, Vette and Mailahn [20] and Garcia investigated some of the issues but there is no existing research on specifying or the provision of guidelines designating where the human operator is best suited in the automated process and where the machine should take full control.

The single-case experimental study was performed on the case study, as described in Chapter 3. The stochastic nature of the make-to-order process, which this case study undertook, limits the extent to which an automation strategy can be used in such applications. Keeping this in mind, a protocol was developed for indicating human-machine collaboration in an automated environment.

During this study, a generic protocol was developed for collaborative decision-making which includes the steps to ensue for developing a protocol as presented in Section 3.3.2. A significant component in developing the protocol, described in Section 3.3, is a Key Performance Indicator (KPI) known as Overall Equipment Effectiveness (OEE), which is used to measure equipment efficiency and performance in an automated environment.

The OEE is a gold standard for measuring performance and standard benchmarks exist for implementing an OEE score as indicated in Section 3.3.1.

Although a world class benchmark for OEE is 85%, as stated in Section 3.3.1, this study adopted an OEE score of 90%. The rationale behind this is that the constraints, namely the water in the storage tank and the number of bottles and caps as presented in Tables 3.1 and 3.2, deemed that a higher percentage than 85% for functioning of the plant was possible. In addition, the manufacturing line for this specific case study is not very long and it functions in an ideal laboratory setup, hence it was decided to adopt a 90% OEE score. It is noteworthy to state that for larger processes the OEE can differ, depending on the application, needs and industry of a company or manufacturer.

With the execution of the SAS program, the output was able to identify some guidelines as to where the machine should perform the task or where a collaboration between the human and machine should take place when referring to the OEE percentage, therefore a protocol was developed for collaborative decision-making in an automated environment. A novel solution that was achieved in this study is that it was able to use a SAS model to be a generic solution allowing for customization of constraints, variables and limitations to suit the needs of the user.

For this particular case study, the limitations accepted as input to the SAS program for determining the TTM's for both approaches as set out in Section 3.11 were as follows:

Constraints:

- Amount of water available, number of bottles and number of caps

Limitations:

- Total liters of water available = 50lt
- Total no of 330ml bottles = 50
- Total no of 500ml bottles = 50
- Total no of caps = 100 (The same size cap is used for both 300ml and 500ml bottles)

Variables: Each customer order had different requirements with respect to number and size of bottles ordered.

Decisions to be made at 50% of constraint levels and at 25% of constraint levels – whether machine continues the process or does it need human intervention which was indicated by taking the constraints and the OEE score into consideration.

The nature of the SAS model is thus that, irrespective of the constraints, variables and limitations, it is possible to customize the program to accept different variables as inputs.

5.4 Chapter Conclusion

The aim of this chapter was to summarize the limitations of existing research followed by a review of the results for each scenario that was tested during the execution of the experiments in SAS. Insights gained from the analysed data was shared and based on the results, the research aimed to show how some of these limitations were overcome.

The results obtained from the execution of the single-case experiment proved the hypothesis that human-machine collaboration contributes to optimizing the production time for the automated production plant in this specific case study.

Chapter 6: Research Contributions and Conclusion

6.1 Introduction

This chapter aims to highlight an original contribution to the existing body of knowledge. The ultimate goal of the study was to explore the importance of human-machine collaboration in a Smart manufacturing environment and to provide a protocol with guidelines/tasks as to where the machine is best to continue a process and where the best fit for human intervention will be in the factory of the future.

The achieved results are showcased, analyzed and discussed and the research goals and objectives of the study are revisited. The conclusion to the research is drawn by identifying the research contributions of the study and finally an emphasis to the future scope of the study is brought to light.

6.2 Summary

The first chapter introduced the research project and stated the problem identified that the research intended to solve. Thereafter an appropriate hypothesis was stated followed by the research aim and list of objectives. The research objectives were used to articulate the project's research methodology. To conclude chapter 1, a layout of the thesis was presented. In Chapter 2 the most relevant contributions of the content that was reviewed were discussed through a review of literature relating to the study. This was done by giving an overview of Industry 4.0 after which Smart manufacturing was introduced, followed by several models employed in the Smart manufacturing environment. This highlighted the research problem identified. The chapter was concluded by examining the limitations of existing research in the relevant field for this particular study. The third chapter focussed on the research methodology employed to provide solutions to the problem which was a single-case experimental study executed on the automated plant. The steps for developing a generic protocol were introduced whereafter the water bottling plant utilized for this study was discussed showcasing the two models identified that were tested using a single-case experimental research approach.

This chapter detailed the two models, namely a fully automated approach versus a human-machine collaborative approach for completing a set of orders. SAS programming was used in the execution of the data collected and provided valuable outputs for the determining of optimization of the automated system. Chapter 4 portrayed the results and conducted an analysis of the results achieved. A detailed discussion of the scenarios tested in Chapter 4, is presented in Chapter 5 which summarized the limitations of existing research followed by a review of the results for each scenario that was tested during the execution of the experiments in SAS. Insights gained from the analysed data was shared and based on the results, the research aimed to show how some of these limitations were overcome by being able to develop a generic protocol for collaborative decision-making in a Smart manufacturing environment.

6.3 Research Aim and Objectives

The aim of this research was to investigate and establish the importance of human intervention in a collaborative decision-making process for the optimum completion of tasks performed by an ICT enabled Smart automated manufacturing system and propose a protocol to determine the tasks/actions best performed by machine, by a human and a collaboration of human and machine.

The main goal of the research was to determine the effects of human-machine collaboration on an automated system as it was established, through an extensive literature review, that the absence of collaborative decision-making processes were recognized as a problem in achieving optimum performance of automated systems and thus the research gap was identified.

6.3.1 Objective 1: Testing, analyzing and validation of the production time for a machine only and the collaboration of a human-and-machine system

Industry 4.0 has revolutionized the way manufacturing was done up to now where production moved away from a make-to-stock approach, which was the traditional approach, to a make-to-order approach [11], [62]. By implementing a mixed-model stochastic method, customers will be able to place orders in accordance with their unique needs for make-to-order products, which meant that the factory relies on a random probability to produce orders as it is difficult to predict what the customer's orders will be [12]. As a result of this, an important concern is the effect that it will have on the interaction between human and machine, as the role of human operators in automated production systems becomes more advanced involving activities of decision-making, interpretation of information and observing real-time data in the manufacturing process [69].

Given the level of human interaction, which is constantly present in automated systems, it becomes important to consider how to incorporate human skillsets in the Industry 4.0 environment for the human to form part of the production control loop [20], [21]. Based on this, it becomes important to consider how a collaborative decision-making process between the human and machine will benefit the automated manufacturing process [4].

The lack of collaborative decision-making in modern Smart factories has been identified as a problem, therefore this study aimed to determine how to implement collaborative decision-making in an automated environment [4]. Several methods were presented, however, to achieve the objectives, a single-case experimental study was implemented [53]. The single-case experimental approach was chosen to prove that a specific theory holds and that all potential doubts are removed. The single-test case experiment was designed and executed using a case study of an existing fully automated water bottling plant to test and prove the theory, which is that the completion time for customer orders received will be optimal when the human and the machine collaborate for the completion of the production process.

Two different scenarios were introduced to determine the impact of collaborative decision-making in the automated system, namely the machine-only approach and, secondly, a collaboration between the human and the machine.

By executing the single-experimental setup through practical examples, it was possible to determine the Total Time to Manufacture (TTM) for each approach. The TTM was the most important outcome to determine for each approach, as it contributed towards identifying which approach played an important part towards optimised production times.

6.3.2 Objective 2: Determining the effects of human-machine collaboration on an automated production system from the testing process.

Several studies previously have looked at the impact of human-machine collaboration on automated systems and some have shown that there is merit in having a human included as part of the production control loop. An example of such a study was performed by Klump, et.al [70] whereby a traffic control problem was introduced to create possible models for collaborative decision-making. In this study it was found that a collaboration between human and machine was the preferred model as it lead to fewer traffic collisions [70]. Another example is a study done by Kruger et. al [47], which found that both humans and machines have strengths and weaknesses and it was argued that a collaborative approach should make use of both sides during the production process.

Based on the results from previous studies, this study was done to determine if a similar pattern arose in this research study through testing the impact of collaborative decision-making in a Smart manufacturing environment using an existing automated water bottling plant as a case study.

Chapter 4 examined the testing that was done on the water bottling plant case study and by interpreting the results, it was established that previous studies had some merit which was proven by this research study. By performing the single-case experimental study, it was possible to determine the effects of human-machine collaboration on an automated production system by comparing the TTM's of the fully automated approach and the human-machine collaboration approach using the experimental results.

The results of this research study indicated the impact of human-machine collaboration which was that the completion time for customer orders were faster as compared to a fully automated mode, and therefore assisted in an optimum production time for the manufacturing process. A journal article presenting the results of this specific research was published by Coetzer, et. al [71].

6.3.3 Objective 3: Developing a protocol with guidelines on tasks/actions best performed by a machine, a human and a collaboration of human and machine.

Based on Objectives 1 and 2, the major drawback from all existing research was that while there has been enough research to show that collaborative decision-making will add value to a manufacturing process, there has never been a protocol or guidelines to state how this can be achieved. The lack of such guidelines or protocols were the reasoning behind developing a protocol for collaborative decision-making in an automated environment in this study.

In achieving the third objective, this research used the Overall Equipment Effectiveness (OEE) approach, which is a key factor in developing a protocol for an automated environment. The OEE is a Key Performance Indicator (KPI) used to measure equipment efficiency and performance [56]. OEE is the gold standard for determining manufacturing productivity and efficiency [58] and an OEE score of 90% was used as a benchmark in this study as a tool in supporting decision-making and equipment effectiveness. A formula for calculating the OEE and how it can be formulated to be included in a SAS program was developed. It was decided that where the OEE is 90% and above, the automated system will

carry out the process and where the OEE falls below 90%, the human should intervene in the production process.
By comparing the results of the two models based on the output from SAS, conclusions could be drawn that assisted in developing a set of guidelines to indicate when a human-machine collaboration should be used during the production process.

Based on the evidence presented, Objective 3 was achieved and the study was able to develop a generic protocol with guidelines on tasks or actions best performed by a machine, a human, and a collaboration of human and machine.

6.4 Research Contributions

This research project developed a protocol for collaborative decision-making in a Smart manufacturing environment. The following contributions from the study are considered to be novel;

6.4.1 Contributions to existing knowledge

Several journal articles and research studies related to the field of human-machine interaction and collaborative decision-making in automated environments were studied starting from 2009 [22] (M. Rother) to 2022 [58] (J. Trout). As discussed in the limitations of the study in Section 2.5, numerous studies were done on how the interaction and communication of the human operator within the automated environment processed can become part of the production process control loop.

With reference to the problem statement identified in Section 1.2, no existing research was found at this time related to providing a protocol or guidelines of where the machine should be more pertinent in the production process or where a collaboration between the human and machine is the more applicable method. The problem identified paved the way for this specific research study to investigate the problem and to put forward a protocol for providing guidelines on where the machine should complete a process and when a human should intervene which will result in the optimization of the automated production process in a Smart manufacturing environment.

A total of four journal articles, as indicated in Section 6.6, indexed in SCOPUS journals related to Computer Science, were published at the time of submitting this thesis.

The paper titled *"Collaborative Decision-Making for Human-Technology Interaction - A Case Study Using an Automated Water Bottling Plant"* [9] added on to the existing research in the field. This paper concentrated on current research performed in this field with a comprehensive literature review, followed by an evaluation of potential models for Human Technology Interaction. The paper then uses the case study of an automated water bottling plant to advance the study in collaborative decision-making and concludes with a discussion on the advantages of collaborative decision-making.

The paper titled *"Devising a Novel Means of Introducing Collaborative Decision-Making to an Automated Water Bottling Plant to Study the Impact of Positive Drift"* [11], examines to develop a novel means of introducing a collaborative decision-making framework to an automated assembly line while determining the impact of collaborative decision-making on positive drift involving humans as well as machines to reduce the impact of positive drift in automated assembly lines.

The methodology used in the study was detailed in the paper titled *"Using a Single Group Experimental Study to Underpin the Importance of Human-in-the-Loop in a Smart Manufacturing Environment"* [72]. The single group experimental study was introduced to investigate an original method for presenting the Human-in-the-Loop to the existing automated plant utilized in this study. The paper identified ways in which the human operator can be kept in the production loop resulting in having a positive contribution to the optimization of production times in an automated manufacturing plant. The methodology for setting up the experimental study was highlighted and the paper was concluded by showcasing the results of the study.

"The Impact of Collaborative Decision-Making in a Smart Manufacturing Environment: Case Study Using an Automated Water Bottling Plant" [71], was a paper written to highlight the results of the study with respect to the case study that was utilized. The results and impact of collaborative decision-making in an automated environment was showcased in this paper.

Based on all the above mentioned articles and the research done during this study, a generic protocol for collaborative decision-making was developed. A novel contribution of the study is that the protocol is able to be customized based on different constraints, variables and limitations for a variety of customer inputs and provide the necessary guidelines for application in similar automated environments.

6.5 Future Work

The Fifth Industrial Revolution, also recognized as Industry 5.0, is a new stage of industrialization which deals specifically with machines and humans and their collaborations to improve processes inside the workplace [73]. It will be worthwhile for a study to look at how the protocol developed in this research study, can be implemented in an Industry 5.0 environment.

An additional study that may possibly be beneficial would be to gain a better understanding of what elements are done better by humans and what elements are best done by machines. Further studies can also take a closer look at why human intervention cannot be avoided, even if better automation processes are implemented in the manufacturing process.

In addition, to verify the SAS model, further testing can be done on real automated industries so as to see how applicable it will be in manufacturing environments.

6.6 Scientific Outcomes

J Coetzer, HJ Vermaak and RB Kuriakose. *"Collaborative Decision-Making for Human-Technology Interaction - A Case Study Using an Automated Water Bottling Plant"* [9]. Journal of Physics Conference: ISSN: 17426588, 10.1088/1742-6596/1577/1/012024, 2020.

J Coetzer, HJ Vermaak and RB Kuriakose. *"Devising a Novel Means of Introducing Collaborative Decision-Making to an Automated Water Bottling Plant to Study the Impact of Positive Drift"* [11] in Lecture Notes in Networks and Systems : ICT Analysis and Applications. Volume 154, pp 661-669. ISBN: 978-981-15-8354-4, doi: 10.1007/978-981-15-8354-4, 2021.

Coetzer J, Vermaak HJ, Kuriakose RB, and Nel G. *"Using a Single Group Experimental Study to Underpin the Importance of Human-in-the-Loop in a Smart Manufacturing Environment"* [72], Advances in Intelligent Systems and Computing. SUSCOM 2022, Volume 464, ISSN:2194-5357, doi: 10.1007/978-981-19-2394-4, 2022.

Coetzer J, Vermaak HJ, Kuriakose RB, and Nel G, 2022. *"The Impact of Collaborative Decision-Making in a Smart Manufacturing Environment: Case Study Using an Automated Water Bottling Plant"* [71], in Lecture Notes in Networks and Systems: Proceedings of Seventh International Congress on Information and Communication Technology. ICICT2022, London, Volume 464, pp 321-332. ISBN 978-981-19-2393-7, ISSN 2367-3370, doi: 10.1007/978-981-19-2394-4_30

References

[1] J. Nagy, J. Oláh, E. Erdei, D. Máté, and J. Popp, “The role and impact of industry 4.0 and the internet of things on the business strategy of the value chain-the case of hungary,” *Sustain.*, vol. 10, no. 10, 2018, doi: 10.3390/su10103491.

[2] M. D. Di Nardo, D. Forino, and T. Murino, “The evolution of man–machine interaction: the role of human in Industry 4.0 paradigm,” *Prod. Manuf. Res.*, vol. 8, no. 1, pp. 20–34, 2020, doi: 10.1080/21693277.2020.1737592.

[3] D. E. Sparrow, K. Kruger, and A. H. Basson, “An architecture to facilitate the integration of human workers in Industry 4.0 environments,” *Int. J. Prod. Res.*, vol. 0, no. 0, pp. 1–19, 2021, doi: 10.1080/00207543.2021.1937747.

[4] M. Klumpp, M. Hesenius, O. Meyer, C. Ruiner, and V. Gruhn, “Production logistics and human-computer interaction—state-of-the-art, challenges and requirements for the future,” *Int. J. Adv. Manuf. Technol.*, 2019, doi: 10.1007/s00170-019-03785-0.

[5] M. Ghobakhloo, “The future of manufacturing industry : a strategic roadmap toward Industry Journal of Manufacturing Technology Management Article information :,” no. June 2018, 2019, doi: 10.1108/JMTM-02-2018-0057.

[6] V. Terziyan, S. Gryshko, and M. Golovianko, “Patented intelligence: Cloning human decision models for Industry 4.0,” *J. Manuf. Syst.*, vol. 48, no. November 2017, pp. 204–217, 2018, doi: 10.1016/j.jmsy.2018.04.019.

[7] M. Xu, J. M. David, and S. H. Kim, “The fourth industrial revolution: Opportunities and challenges,” *Int. J. Financ. Res.*, vol. 9, no. 2, pp. 90–95, 2018, doi: 10.5430/ijfr.v9n2p90.

[8] R. Y. Zhong, X. Xu, E. Klotz, and S. T. Newman, “Intelligent Manufacturing in the Context of Industry 4.0: A Review,” *Engineering*, vol. 3, no. 5, pp. 616–630, 2017, doi: 10.1016/J.ENG.2017.05.015.

[9] J. Coetzer, R. B. Kuriakose, and H. J. Vermaak, “Collaborative Decision Making for Human Technology Interaction - A Case Study Using an Automated Water Bottling Plant,” *J. Physics. Conf. Ser.*, 2020, doi: 10.1088/1742-6596/1577/1/012024.

[10] N. Kumar and S. C. Lee, “Technological Forecasting & Social Change Human-machine interface in smart factory : A systematic literature review,” *Technol. Forecast. Soc. Chang.*, vol. 174, no. October 2021, p. 121284, 2022, doi: 10.1016/j.techfore.2021.121284.

[11] J. Coetzer, R. Kuriakose, and H. Vermaak, “Devising a Novel Means of Introducing Collaborative Decision-Making to an Automated Water Bottling Plant to Study the Impact of Positive Drift,” in *Lecture Notes in Networks and Systems 154ICT Analysis and Applications*, Volume 154., S. Fong, M. Zhuhai, A. Joshi, and N. Dey, Eds. Singapore: Springer Nature Singapore Pte Ltd. 2021, 2020, pp. 661–669.

[12] R. B. Kuriakose and H. J. Vermaak, “Customized Mixed Model Stochastic Assembly Line Modelling Using Simulink,” *Interational J. Simul. Syst. Sci. Technol.*, pp. 2–7, 2019, doi: 10.5013/IJSSST.a.20.S1.06.

[13] R. Kuriakose and H. Vermaak, “Optimization of a Customized Mixed Model Assembly Using Optimization of a Customized Mixed Model Assembly Using MATLAB / Simulink,” *J. or Physics. Conf. Ser.*, vol. 1201, no. 012017, 2019, doi: 10.1088/1742-6596/1201/1/012017.

[14] S. Vaidya, P. Ambad, and S. Bhosle, “Industry 4 . 0 – A Glimpse Costing models for capacity optimization in Industry 4 . 0 : Trade-off between used capacity and operational efficiency,” *Procedia Manuf.*, vol. 20, no. November, pp. 233–238, 2018, doi: 10.1016/j.promfg.2018.02.034.

[15] R. B. Kuriakose and H. J. Vermaak, “Optimization of a Customized Mixed Model Assembly Using MATLAB/Simulink,” *J. Phys. Conf. Ser.*, vol. 1201, no. 1, 2019.

[16] A. Kusiak, “Smart manufacturing,” *Int. J. Prod. Res.*, vol. 56, no. 1–2, pp. 508–517, 2018, doi: 10.1080/00207543.2017.1351644.

[17] T. Bauernhansl, S. Kondoh, S. Kumara, L. Monostori, and B. Ka, “CIRP Annals - Manufacturing Technology Cyber-physical systems in manufacturing,” vol. 65, pp. 621–641, 2016, doi: 10.1016/j.cirp.2016.06.005.

[18] M. P. Pacaux-Lemoine, D. Trentesaux, G. Zambrano Rey, and P. Millot, “Designing intelligent manufacturing systems through Human-Machine Cooperation principles: A human-centered approach,” *Comput. Ind. Eng.*, vol. 111, pp. 581–595, 2017, doi: 10.1016/j.cie.2017.05.014.

[19] D. Feil-seifer and M. J. Matari, “Encyclopedia of Complexity and Systems Science,” *Encycl. Complex. Syst. Sci.*, no. April, pp. 0–20, 2009, doi: 10.1007/978-0-387-30440-3.

[20] I. A. R. J. Torn, N. J. Pulles, and H. Schiele, “Industry 4.0 and how purchasing can progress and benefit from the fourth industrial revolution,” *27th Annu. IPSERA Conf. 2018, Athens, Greece*, vol. 0, p. 16, 2018.

[21] P. Ponsa, R. Vilanova, and B. Amante, “Human Intervention and Interface Design in Automation Systems,” *Int. J. Comput. Commun. Control*, vol. 6, no. 1, p. 166, Mar. 2010, doi: 10.15837/ijccc.2011.1.2211.

[22] M. Rother, *Toyota Kata: Managing People for Improvement, Adaptiveness and Superior Results*. Education, McGraw-Hill, 2009.

[23] S. Pan, E. Ballot, G. Q. Huang, and B. Montreuil, “Physical Internet and interconnected logistics services: research and applications,” *Int. J. Prod. Res.*, vol. 55, no. 9, pp. 2603–2609, 2017, doi: 10.1080/00207543.2017.1302620.

[24] J.-M. Hoc, “From human-machine interaction to human-machine cooperation,” *Ergonomics*, vol. 43, no. 7, pp. 833–843, 2000.

[25] K. Kasemsap, “The Fundamentals of Human- Computer Interaction,” pp. 524–526, doi: 10.4018/978-1-5225-7368-5.ch039.

[26] F. Ren and Y. Bao, *A Review on Human-Computer Interaction and Intelligent Robots*, vol. 19, no. 1. 2020.

[27] L. Liu and M. Ozsu, “Human-Computer Interaction,” in *Human-Computer Interaction*, E. of D. Systems, Ed. Springer, Boston, 2009.

[28] J. LaViola, E. Kruijff, R. McMahan, D. Bowman, and I. Poupyrev, *3D User Interfaces: Theory and Practice, 2nd Edition*. 2017.

[29] J. Boasberg *et al.*, “What is Human-Machine Interaction,” *Duke Law J.*, vol. 1, no. 1, pp. 1–13, 2019, doi: 10.1017/CBO9781107415324.004.

[30] C. Series, “Human computer interaction in transport , a systematic literature review,” 2019, doi: 10.1088/1742-6596/1409/1/012002.

[31] D. Bachmann, F. Weichert, and G. Rinkenauer, “Review of three-dimensional human-computer interaction with focus on the leap motion controller,” *Sensors (Switzerland)*, vol. 18, no. 7, pp. 1–39, 2018, doi: 10.3390/s18072194.

[32] J. Coetzer, “Application of HCI design principles in overcoming information illiteracy: Case of a M-health application for a rural community in South Africa,” in *2018 International Conference on Intelligent and Innovative Computing Applications, ICONIC 2018*, 2019, doi: 10.1109/ICONIC.2018.8601289.

[33] D. Zuehlke, “SmartFactory - Towards a factory-of-things,” vol. 34, pp. 129–138, 2010, doi: 10.1016/j.arcontrol.2010.02.008.

[34] P. Automation, “Differences between SCADA and HMI,” 2018. [Online]. Available: https://info.premierautomation.com/blog/differences-between-scada-and-hmi.

[35] D. Krambeck, “An Introduction to SCADA systems,” 2015. [Online]. Available: https://www.allaboutcircuits.com/technical-articles/an-introduction-to-scada-systems/.

[36] Q. Ke, J. Liu, M. Beannamoun, S. An, and F. Sohel, “Computer Vision for Assistive Health care,” in *Computer Viision for Human-Machine Interaction*, 2018, pp. 127–145.

[37] Z. Yunfeng and P. Mingming, “Application and Prospect of Human-Machine Interaction in Power System Application and Prospect of Human-Machine Interaction in Power System,” *J. Physics. Conf. Ser.*, vol. 1345, no. 032094, 2019, doi: 10.1088/1742-6596/1345/3/032094.

[38] A. Setiawan, Sugeng, K. I. Koesoema, S. Bakhri, and J. Aditya, “The SCADA system using PLC and HMI to improve the effectiveness and efficiency of production processes The SCADA system using PLC and HMI to improve the effectiveness and efficiency of production processes,” *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 550, 2019, doi: 10.1088/1757-899X/550/1/012008.

[39] D. Wollherr and M. Buss, “Human-Robot Collaboration : a Survey .,” no. March, 2008, doi: 10.1142/S0219843608001303.

[40] L. Norros, E. Kaasinen, J. Plomp, and P. Rämä, “Human-technology interaction research and design: VTT roadmap,” *VTT Tied. - Valt. Tek. Tutkimusk.*, no. 2220, pp. 3–118, 2003.

[41] P. A. Hancock and M. H. Chignell, “On human factors,” in *Global Perspectives on the Ecology of Human-Machine Systems*, vol. 1, J. Flach, P. A. Hancock, J. K. Caird, and K. Vicente, Eds. Lawrence Erlbaum, 1995, pp. 14–53.

[42] P. P. Rau, Y. Li, and J. Liu, “Effects of a Social Robot ’ s Autonomy and Group Orientation on Human Decision-Making,” vol. 2013, pp. 6–8, 2013.

[43] N. Ulibarri, “Collaborative model development increases trust in and use of scientific information in environmental decision-making,” *Environ. Sci. Policy*, vol. 82, no. February, pp. 136–142, 2018, doi: 10.1016/j.envsci.2018.01.022.

[44] N. A. Noordin, U. S. Bititci, and R. Van Der Meer, “Review on collaborative decision making in supply chain: The relationship between e-collaboration technology and development of inter-organizational trust,” *IFIP Adv. Inf. Commun. Technol.*, vol. 384 AICT, pp. 326–341, 2012, doi: 10.1007/978-3-642-33980-6_37.

[45] D. Wollherr and M. Buss, “Human-Robot Collaboration : a Survey .,” *Int. J. Humanoid Robot.*, vol. 5, no. March, 2008, doi: 10.1142/S0219843608001303.

[46] B. Note, O. By, and T. H. E. French, “AI , AUTOMATION , AND THE FUTURE OF WORK : TEN THINGS TO SOLVE FOR,” in *Tech4Good Summit*, 2018, pp. 1–7.

[47] J. Kruger, T. K. Lien, and A. Verl, “Cooperation of human and machines in assembly lines,” vol. 58, pp. 628–646, 2009, doi: 10.1016/j.cirp.2009.09.009.

[48] P. R. Müller, D. Fh, M. Vette, and D. O. Mailahn, “Process-oriented task assignment for assembly processes with human-robot interaction,” *Procedia CIRP*, vol. 44, pp. 210–215, 2016, doi: 10.1016/j.procir.2016.02.080.

[49] M. A. Ruiz Garcia, R. Rojas, L. Gualtieri, E. Rauch, and D. Matt, “A human-in-the-loop cyber-physical system for collaborative assembly in smart manufacturing,” *Procedia CIRP*, vol. 81, pp. 600–605, 2019, doi: 10.1016/j.procir.2019.03.162.

[50] P. Ponsa, R. Vilanova, and M. Diaz, “Gemma guide approach for the introduction of the human operator into the automation cycle,” *IFAC Proc. Vol.*, vol. 7, no. PART 1, pp. 285–290, 2006, doi: 10.3182/20060621-3-es-2905.00050.

[51] E. Marsden and C. J. Torgerson, “Oxford Review of Education Single group , pre- and post-test research designs : Some methodological concerns,” no. October, 2012, doi: 10.2307/41702779.

[52] A. Krasny-pacini and J. Evans, “ScienceDirect Single-case experimental designs to assess intervention effectiveness in rehabilitation : A practical guide,” *Ann. Phys. Rehabil. Med.*, vol. 61, no. 3, pp. 164–179, 2018, doi: 10.1016/j.rehab.2017.12.002.

[53] M. Olivier, *Information Technology Research*, 3rd Editio. Pretoria: Van Schaik Publishers, 2009.

[54] O. Of and I. Network, “Industrial Network Protocols,” pp. 121–169, doi: 10.1016/B978-0-12-420114-9/00006-X.

[55] N. Arjun, “Manufacturing automation protocol and it’s expectations,” *SolutionBuggy*. [Online]. Available: https://www.linkedin.com/pulse/manufacturing-automation-protocol-its-expectations-arjun-n-/.

[56] C. Ng, M. Enrique, and H. Korner, “applied sciences Overall Equipment E ff ectiveness : Systematic Literature Review and Overview of Di ff erent Approaches,” *Www.Mdpi.Com/Journal/Applsci*, no. 1988, 2020.

[57] P. G. Yazdi, A. Azizi, and M. Hashemipour, “An empirical investigation of the relationship between overall equipment efficiency (OEE) and manufacturing sustainability in industry 4.0 with time study approach,” *Sustain.*, vol. 10, no. 9, 2018, doi: 10.3390/su10093031.

[58] J. Trout, “What is Overall Equipment Effectiveness (OEE)?,” *ReliablePlant*, 2022. [Online]. Available: https://www.reliableplant.com/Read/11785/overall-equipment-effectiveness. [Accessed: 22-Nov-2022].

[59] Symestic, “The OEE Blog for Your Success.” [Online]. Available: https://www.symestic.com/en-us/oee. [Accessed: 22-Nov-2022].

[60] L. Foulloy, V. Clville, and L. Berrah, “A fuzzy temporal approach to the Overall Equipment Effective measurement,” *Comput. Ind. Eng.*, vol. 127, pp. 103–115, 2019, doi: 10.1016/j.cie.2018.11.043.

[61] A. Munoz-Villamizar, J. Santos, J. Montoya-Torres, and C. Jaca, “Using OEE to evaluate the effectiveness of urban freight transportation system: A case study,” *Int. J. Prod. Econ.*, vol. 197, pp. 232–242, 2018, doi: 10.1016/j.ijpe.2018.01.011.

[62] R. B. Kuriakose and H. J. Vermaak, “Designing a Simulink model for a mixed model stochastic assembly line: A case study using a water bottling plant,” *J. Discret. Math. Sci. Cryptogr.*, vol. 23, no. 2, pp. 329–336, 2020.

[63] C. Series, “Machine to Machine Communication Protocol for SMART Manufacturing Units Machine to Machine Communication Protocol for SMART Manufacturing Units,” 2020, doi: 10.1088/1742-6596/1577/1/012047.

[64] R. M. Van Der Knijff, “Control systems / SCADA forensics , what ’ s the difference ?,” *Digit. Investig.*, vol. 11, no. 3, pp. 160–174, 2014, doi: 10.1016/j.diin.2014.06.007.

[65] P. Zheng *et al.*, “Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives,” *Front. Mech. Eng.*, vol. 13, no. 2, pp. 137–150, 2018, doi: 10.1007/s11465-018-0499-5.

[66] A. Chhabra, “The Relation between IIoT, SCADA and HMI Explained,” *Industrial Software*, 2019. [Online]. Available: https://blog.se.com/industrial-software/2019/05/28/the-relation-between-iiot-scada-and-hmi-explained/.

[67] Univeristy of IOWA, “Statistical Analysis System (SAS),” *Information Technology Services*, 2022. [Online]. Available: https://its.uiowa.edu/sas#:~:text=Statistical Analysis System (SAS) is,analysis%2C econometrics and data mining.

[68] G. Michalos *et al.*, “Seamless human robot collaborative assembly – An automotive case study,” *Mechatronics*, vol. 55, no. September, pp. 194–211, 2018, doi: 10.1016/j.mechatronics.2018.08.006.

[69] P. Kumar *et al.*, “Journal of Industrial Information Integration Industry 5 . 0 : A survey on enabling technologies and potential applications ☆,” *J. Ind. Inf. Integr.*, vol. 26, no. August 2021, p. 100257, 2022, doi: 10.1016/j.jii.2021.100257.

[70] M. Klumpp, M. Hesenius, O. Meyer, C. Ruiner, and V. Gruhn, “Production logistics and human-computer interaction—state-of-the-art, challenges and requirements for the future,” *Int. J. Adv. Manuf. Technol.*, vol. 105, no. 9, pp. 3691–3709, 2019, doi: 10.1007/s00170-019-03785-0.

[71] J. Coetzer, H. J. Vermaak, R. B. Kuriakose, and G. Nel, “The Impact of Collaborative Decision-Making in a Smart Manufacturing Environment: Case Study Using an Automated Water Bottling Plant,” in *Proceedings of Seventh International Congress on Information and Communication Technology. Lecture Notes in Networks and Systems*, Springer, Singapore, 2022, pp. 321–332.

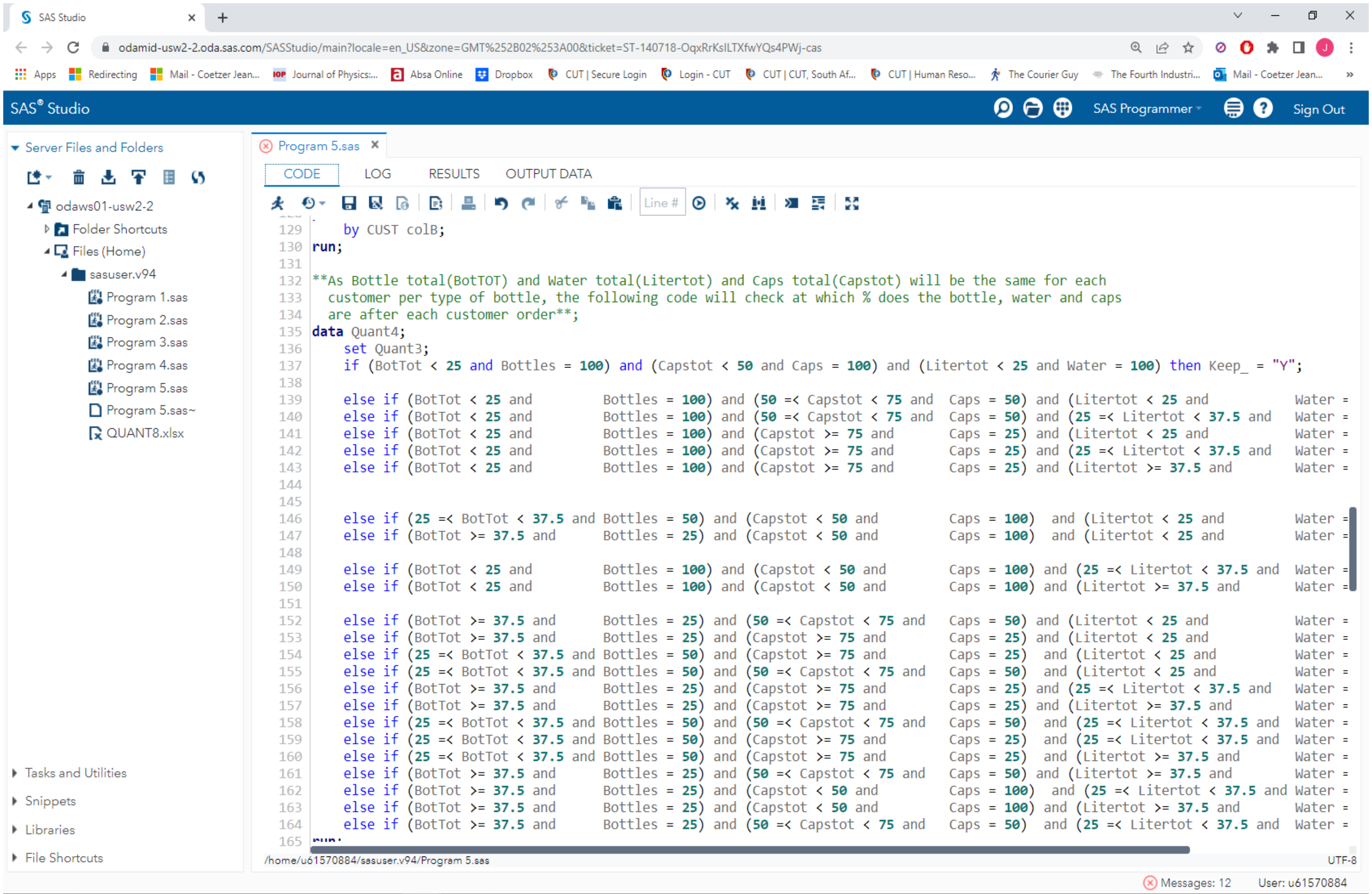
[72] J. Coetzer, H. J. Vermaak, R. B. Kuriakose, and Nel, “Using a Single Group Experimental Study to Underpin the Importance of Human-in-the-Loop in a Smart Manufacturing Environment,” in *Lecture Notes in Networks and Systems 154ICT Analysis and Applications*, Springer, Singapore, 2022, pp. 375–384.

[73] M. Ruggieri, “The innovation behind the fifth industrial revolution,” *The Manufacturer*, 2022. [Online]. Available: https://www.themanufacturer.com/articles/the-innovation-behind-the-industrial-revolution/#:~:text=The Fifth Industrial Revolution%2C also,enhance processes within the workplace. [Accessed: 15-Jan-2023].

Central University of Technology, Free State

Appendix A

A Snapshot of the SAS code for determining the different combinations of constraints



```
   by CUST colB;
run;

**As Bottle total(BotTOT) and Water total(Litertot) and Caps total(Capstot) will be the same for each
 customer per type of bottle, the following code will check at which % does the bottle, water and caps
 are after each customer order**;
data Quant4;
   set Quant3;
   if (BotTot < 25 and Bottles = 100) and (Capstot < 50 and Caps = 100) and (Litertot < 25 and Water = 100) then Keep_ = "Y";

   else if (BotTot < 25 and         Bottles = 100) and (50 =< Capstot < 75 and  Caps = 50) and (Litertot < 25 and        Water =
   else if (BotTot < 25 and         Bottles = 100) and (50 =< Capstot < 75 and  Caps = 50) and (25 =< Litertot < 37.5 and Water =
   else if (BotTot < 25 and         Bottles = 100) and (Capstot >= 75 and       Caps = 25) and (Litertot < 25 and        Water =
   else if (BotTot < 25 and         Bottles = 100) and (Capstot >= 75 and       Caps = 25) and (25 =< Litertot < 37.5 and Water =
   else if (BotTot < 25 and         Bottles = 100) and (Capstot >= 75 and       Caps = 25) and (Litertot >= 37.5 and     Water =


   else if (25 =< BotTot < 37.5 and Bottles = 50) and (Capstot < 50 and         Caps = 100)  and (Litertot < 25 and      Water =
   else if (BotTot >= 37.5 and      Bottles = 25) and (Capstot < 50 and         Caps = 100)  and (Litertot < 25 and      Water =

   else if (BotTot < 25 and         Bottles = 100) and (Capstot < 50 and        Caps = 100) and (25 =< Litertot < 37.5 and Water =
   else if (BotTot < 25 and         Bottles = 100) and (Capstot < 50 and        Caps = 100) and (Litertot >= 37.5 and    Water =

   else if (BotTot >= 37.5 and      Bottles = 25) and (50 =< Capstot < 75 and   Caps = 50) and (Litertot < 25 and        Water =
   else if (BotTot >= 37.5 and      Bottles = 25) and (Capstot >= 75 and        Caps = 25) and (Litertot < 25 and        Water =
   else if (25 =< BotTot < 37.5 and Bottles = 50) and (Capstot >= 75 and        Caps = 25)  and (Litertot < 25 and       Water =
   else if (25 =< BotTot < 37.5 and Bottles = 50) and (50 =< Capstot < 75 and   Caps = 50)  and (Litertot < 25 and       Water =
   else if (BotTot >= 37.5 and      Bottles = 25) and (Capstot >= 75 and        Caps = 25) and (25 =< Litertot < 37.5 and Water =
   else if (BotTot >= 37.5 and      Bottles = 25) and (Capstot >= 75 and        Caps = 25) and (Litertot >= 37.5 and     Water =
   else if (25 =< BotTot < 37.5 and Bottles = 50) and (50 =< Capstot < 75 and   Caps = 50)  and (25 =< Litertot < 37.5 and Water =
   else if (25 =< BotTot < 37.5 and Bottles = 50) and (Capstot >= 75 and        Caps = 25)  and (25 =< Litertot < 37.5 and Water =
   else if (25 =< BotTot < 37.5 and Bottles = 50) and (Capstot >= 75 and        Caps = 25)  and (Litertot >= 37.5 and    Water =
   else if (BotTot >= 37.5 and      Bottles = 25) and (50 =< Capstot < 75 and   Caps = 50) and (Litertot >= 37.5 and     Water =
   else if (BotTot >= 37.5 and      Bottles = 25) and (Capstot < 50 and         Caps = 100)  and (25 =< Litertot < 37.5 and Water =
   else if (BotTot >= 37.5 and      Bottles = 25) and (Capstot < 50 and         Caps = 100) and (Litertot >= 37.5 and    Water =
   else if (BotTot >= 37.5 and      Bottles = 25) and (50 =< Capstot < 75 and   Caps = 50)  and (25 =< Litertot < 37.5 and Water =
run;
```

Appendix B

Appendix B shows the full results for Scenario 4 – Scenario 6 as executed during the single-case experiment of the study.

B1: Scenario 4 – Automated and HMI approach with bottles and caps as constraints

Table B1.1 indicates the customer requirements for filling and capping the 330ml and 500 ml bottles for Scenario 4. For this scenario, a total of 39 bottles need filling and capping.

B1 1. Customer requirements for the 300ml and 500ml bottles - Scenario 4

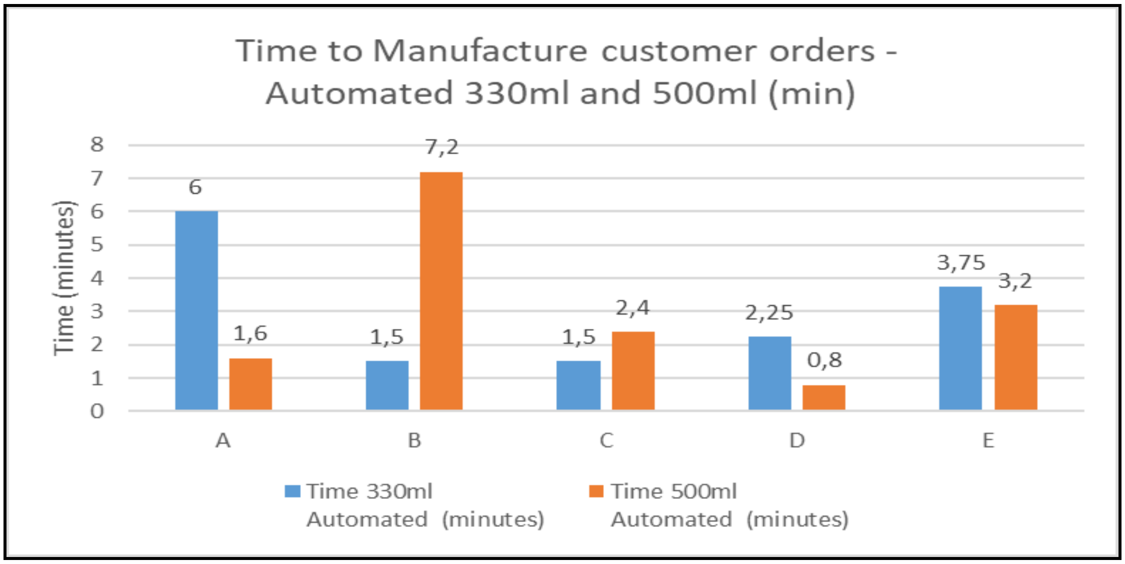
Customer	No of 330ml caps, bottles	No of 500ml caps, bottles	Total No of Caps & Bottles
A	8	2	10
B	2	9	11
C	2	3	5
D	3	1	4
E	5	4	9
TOTAL NO OF CAPS & BOTTLES	20	19	39

B1: Scenario 4 – Filling and capping the 330ml and 500ml bottles: Automated mode

As indicated in Table B1.2, a total of 20 of the 330ml bottles must be filled and capped for this specific customer order. Figure B1.3 illustrates the time to manufacture the order and indicates the number of bottles and caps needed for each order.

B1 2. Manufacturing time for filling and capping 330ml and 500ml bottles: Automated

Customer	No of 330ml caps, bottles	No of 500ml caps, bottles	Total No of Caps & Bottles	Time 330ml Automated (minutes)	Time 500ml Automated (minutes)
A	8	2	10	6	1,6
B	2	9	11	1,5	7,2
C	2	3	5	1,5	2,4
D	3	1	4	2,25	0,8
E	5	4	9	3,75	3,2
TOTAL	20	19	39	15	15,2



B1 3. Diagram presenting the manufacturing time of customer order for 300ml and 500ml bottles: Automated

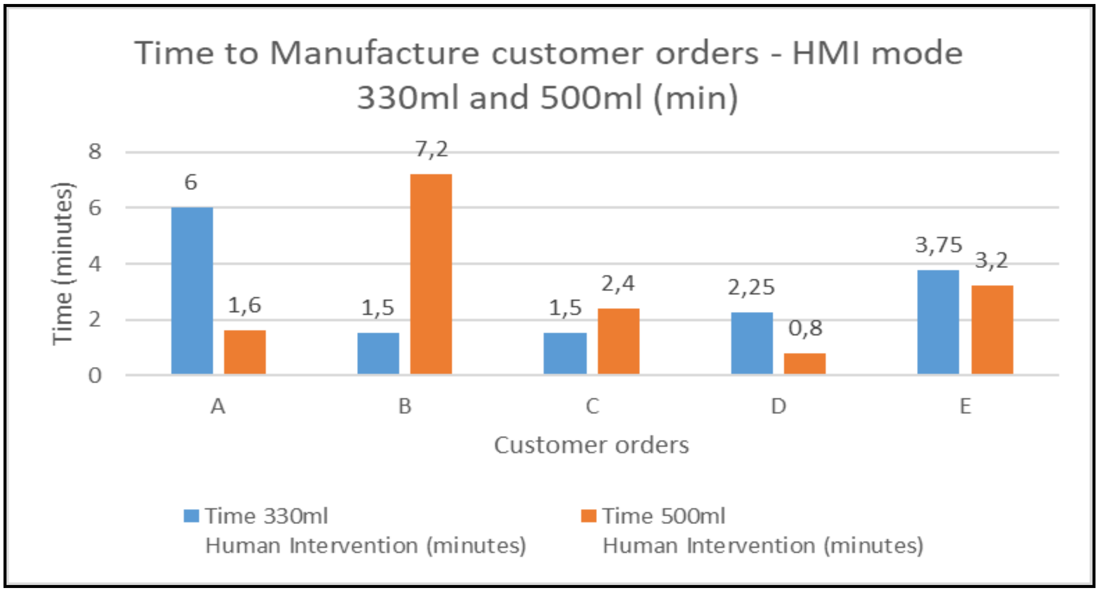
B1: Scenario 4 – Filling and capping the 330ml and 500ml bottles: HMI mode

The same set of orders, as indicated in Table B1.4 for the automated mode, is applied for the execution of the experiment in HMI mode.

B1 4. Manufacturing time for filling and capping the 330ml and 500ml bottles: HMI mode

Customer	Total No of Caps & Bottles	Time to manufacture 330ml Human Intervention (minutes)	Time to manufacture 500ml Human Intervention (minutes)
A	10	6	1,6
B	11	1,5	7,2
C	5	1,5	2,4
D	4	2,25	0,8
E	9	3,75	3,2
TOTAL	39	15	15,2

The manufacturing time for the customer order in Scenario 4 using the HMI mode can be seen in Figure B1.5.



B1 5. Diagram presenting the manufacturing time of Scenario 4 in HMI mode

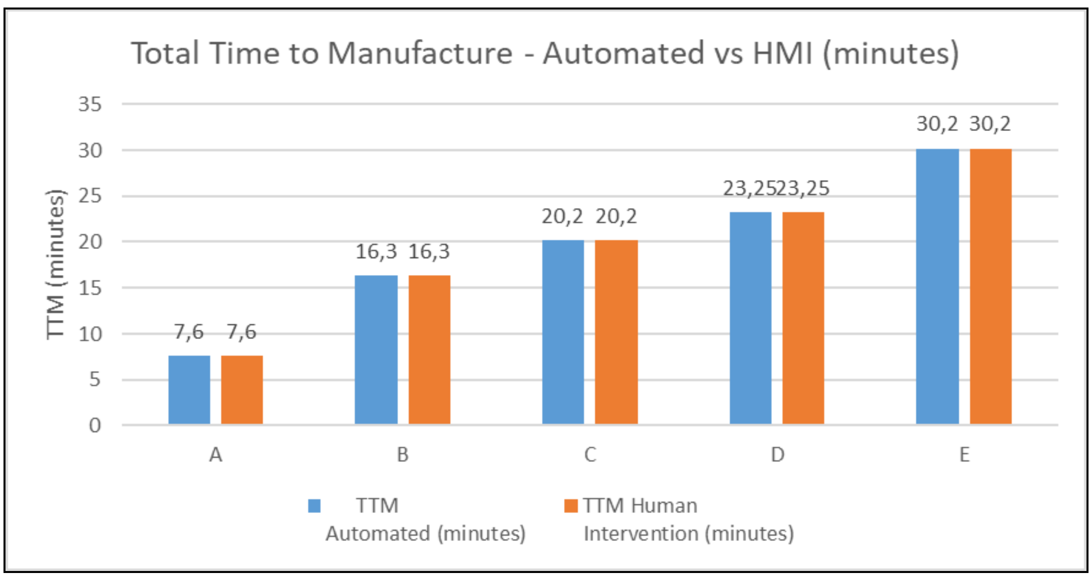
B1: Scenario 4 – TTM for manufacturing in Automated mode vs HMI mode

As can be seen from the results showcased in Table B1.6 the TTM for both modes were the same for this scenario.

B1 6. TTM for filling and capping: Automated vs HMI – Scenario 4 (HMI

Customer	Total No of Caps & Bottles	TTM Automated (minutes)	TTM Human Intervention (minutes)	Total Lt used	OEE %	Human Intervention
A	10	7,6	7,6	3,64	100%	No
B	11	16,3	16,3	8,8	100%	No
C	5	20,2	20,2	10,96	100%	No
D	4	23,25	23,25	12,45	96,02%	No
E	9	30,2	30,2	16,1	90,08%	No

The total amount of water used for filling and capping the 39 bottles for this customer order were 16 liters. The constraints never reached 50% which means that the machine could complete the order without human intervention. The machine efficiency as portrayed by the OEE%, stays above 90% for the specific order, therefore it can be deduced that the machine is in full control for the duration of completing this order and completed the order in 30,2 minutes. Figure B1.7 graphically shows the results for Scenario 4.



B1 7. TTM for filling and capping: Automated mode vs HMI mode - Scenario 4.

B2: Scenario 5 –Bottles and caps as constraints

Table B2.1 indicates the customer order requirements for Scenario 5. The following section will display the results for executing Scenario 5.

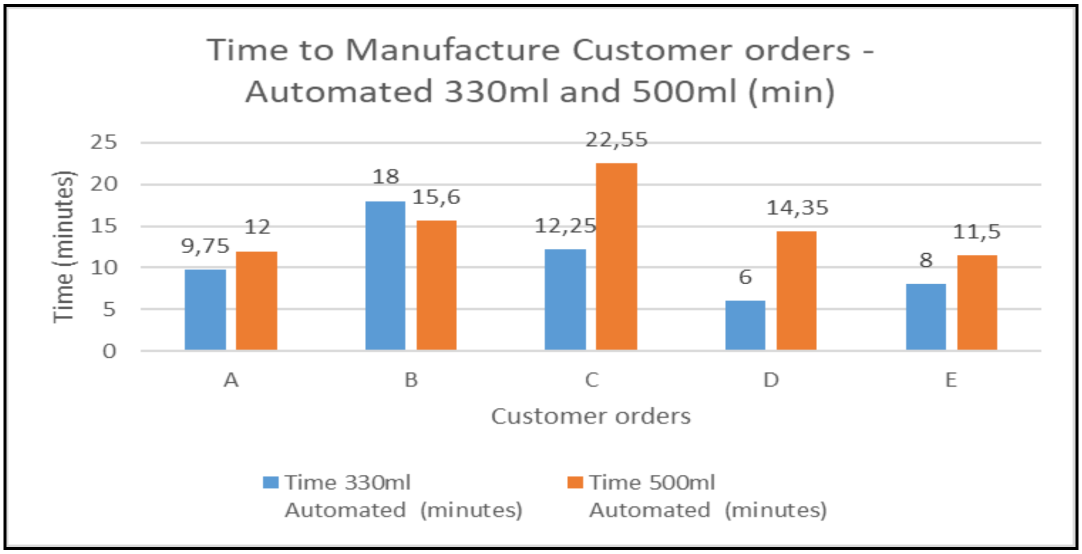
B2 1. Customer requirements for the 330ml and 500ml bottles – Scenario 5

Customer	No of 330ml caps, bottles	No of 500ml caps, bottles	Total No of Caps & Bottles
A	13	15	28
B	18	12	30
C	7	11	18
D	3	7	10
E	4	5	9
TOTAL NO OF BOTTLES AND CAPS	45	50	95

B2: Scenario 5 – Filling and capping 330ml and 500ml bottles: Automated mode

B2 2. Time to fill and cap customer order for 330ml and 500ml bottles: Automated

Customer	No of 330ml caps, bottles	No of 500ml caps, bottles	Total No of Caps & Bottles	Time 330ml Automated (minutes)	Time 500ml Automated (minutes)
A	13	15	28	9,75	12
B	18	12	30	18	15,6
C	7	11	18	12,25	22,55
D	3	7	10	6	14,35
E	4	5	9	8	11,5
TOTAL	45	50	95	54	76



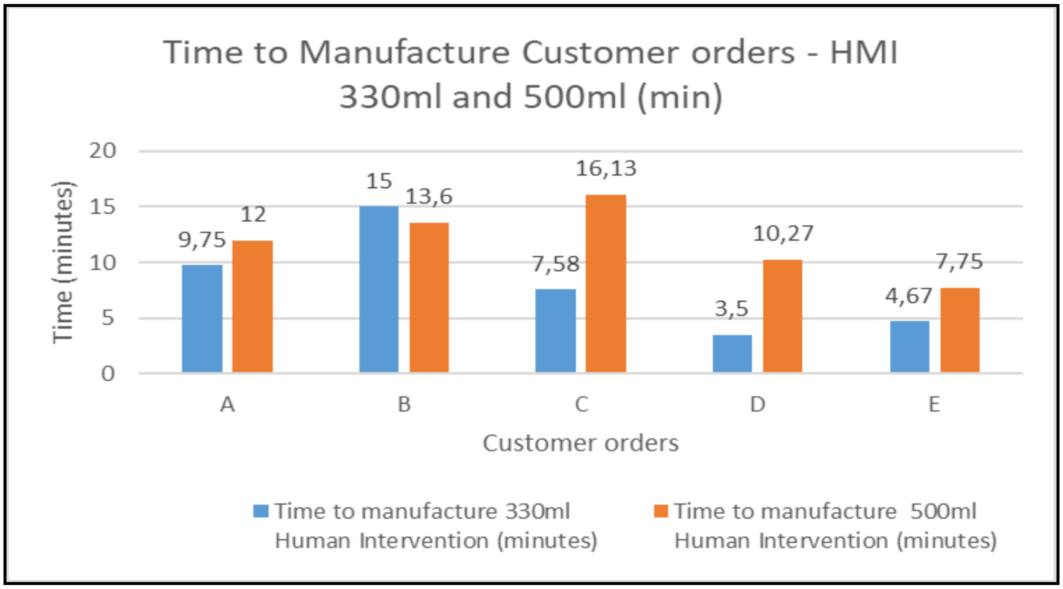
B2 3. Diagram presenting the manufacturing time for 330ml and 500ml bottles for Scenario 5: Automated mode

B2: Scenario 5 – Filling and capping 330ml and 500ml bottles: HMI mode

Table B2.4 presents the time to fill and cap the 330ml and 500ml bottles for customer order in Scenario 5 when the HMI mode is executed.

B2 4. Filling and capping time for the 300ml and 500ml bottles for Scenario 5: HMI mode

Customer	Total No of Caps & Bottles	Time to manufacture 330ml Human Intervention (minutes)	Time to manufacture 500ml Human Intervention (minutes)
A	28	9,75	12
B	30	15	13,6
C	18	7,58	16,13
D	10	3,5	10,27
E	9	4,67	7,75
TOTAL	95	40,5	59,75



B2 5. Diagram presenting the manufacturing time for 330ml and 500ml bottles for Scenario 5: HMI mode

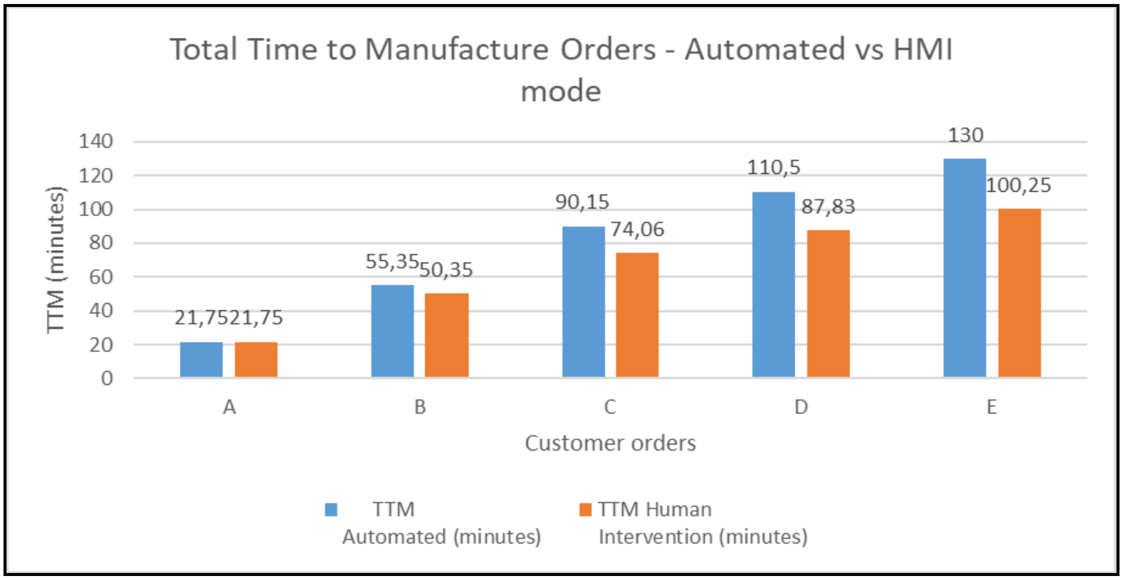
B2: Scenario 5 – TTM for manufacturing 330ml and 500ml bottles: Automated mode vs HMI mode

Table B2.6 shows the TTM's of the customer order for Scenario 5, the amount of bottles and caps used and where the human should intervene in the process.

B2 6. TTM of customer order of 330ml and 500ml bottles: Automated vs HMI mode – Scenario 5

Customer	Total no of caps and bottles	TTM Automated (minutes)	TTM Human Intervention (minutes)	Total Lt used	OEE %	Human Intervention
A	28	21,75	21,75	11,79	100%	No
B	30	55,35	50,35	23,73	90,97%	No
C	18	90,15	74,06	31,54	82,15%	Yes
D	10	110,5	87,83	36,03	79,48%	Yes
E	9	130	100,25	39,85	77,11%	Yes

For this specific order, the total amount of liters used to fill and cap the 330ml and 500ml bottles were almost 40 liters. The number of bottles and caps needed were 95, as identified in Table B2.6. The TTM for completing this order in automated and human intervention mode can be perceived in Figure B2.7.



B2 7. Diagram showing the TTM of filling and capping customer orders for 330ml and 500ml bottles: Automated vs HMI mode – Scenario 5

As graphically pointed out in Figure B2.7, the TTM for the Automated approach to complete the customer order for Scenario 5, was 130 minutes in contrast to the Human-Intervention approach completed the order in 100,25 minutes.

B3: Scenario 6 – Bottles and Caps as Constraints

Table B3.1 specifies the customer order requirements for Scenario 6. The following section will display the results obtained after executing Scenario 6.

B3 1. Customer requirements for the 330ml and 500ml bottles – Scenario 6

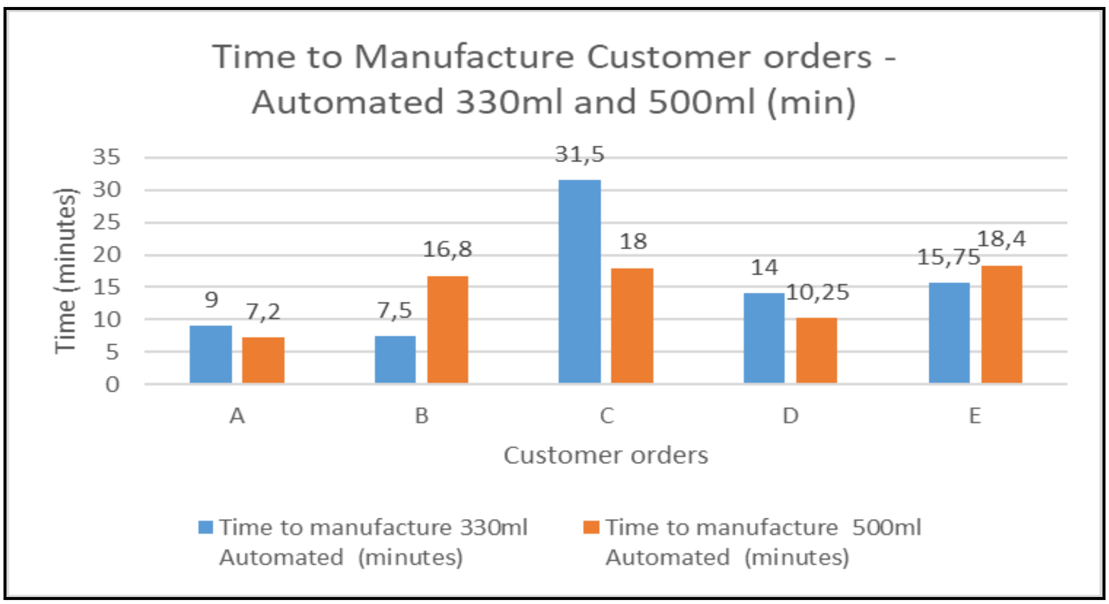
Customer	No of 330ml caps, bottles	No of 500ml caps, bottles	Total No of Caps & Bottles
A	12	9	21
B	10	16	26
C	18	10	28
D	7	5	12
E	7	8	15
TOTAL	54	48	102

B3: Scenario 6 – Filling and capping 330ml and 500ml bottles: Automated mode

B3 2. Manufacturing time of customer order Scenario 6 for 330ml and 500ml bottles: Automated mode

Customer	No of 330ml caps, bottles	No of 500ml caps, bottles	Total No of Caps & Bottles	Time to manufacture 330ml Automated (minutes)	Time to manufacture 500ml Automated (minutes)
A	12	9	21	9	7,2
B	10	16	26	7,5	16,8
C	18	10	28	31,5	18
D	7	5	12	14	10,25
E	7	8	15	15,75	18,4
TOTAL	54	48	102	77,75	70,65

The results in Table B3.2 indicates the manufacturing time to complete the customer order for Scenario 6 in Automated Mode.

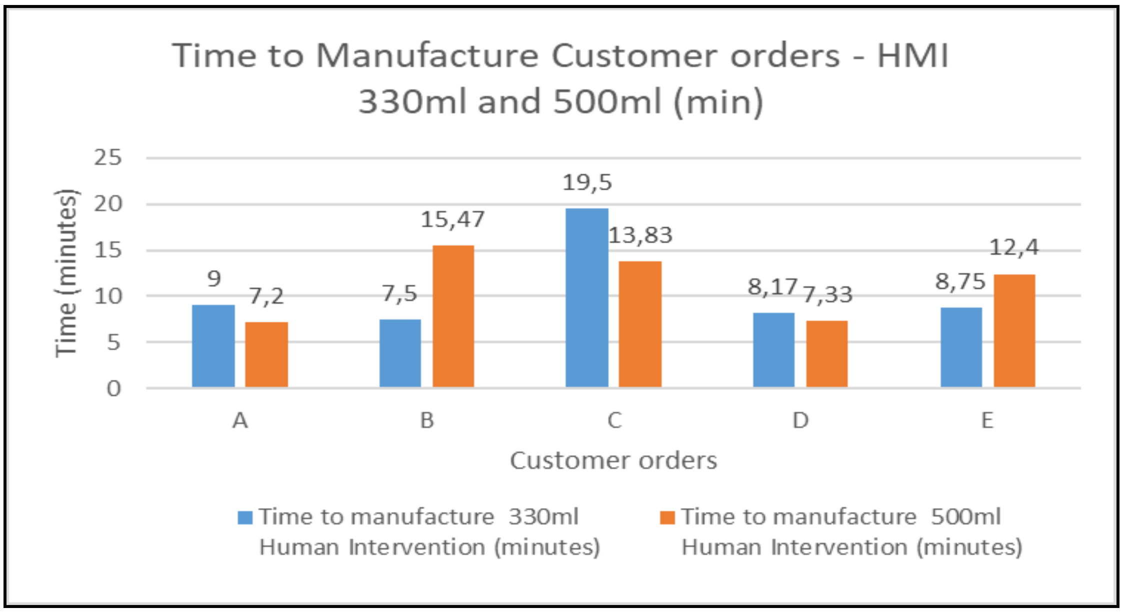


B3 3. Manufacturing time for 330ml and 500ml bottles for Scenario 6: Automated mode

B3: Scenario 6 – Filling and capping 330ml and 500ml bottles: HMI mode

B3 4. Time to manufacture 330ml and 500ml bottles for Scenario 6: HMI mode

Customer	No of 500ml caps, bottles	Time to manufacture 330ml Human Intervention (minutes)	Time to manufacture 500ml Human Intervention (minutes)
A	9	9	7,2
B	16	7,5	15,47
C	10	19,5	13,83
D	5	8,17	7,33
E	8	8,75	12,4
TOTAL	48	52,92	56,23



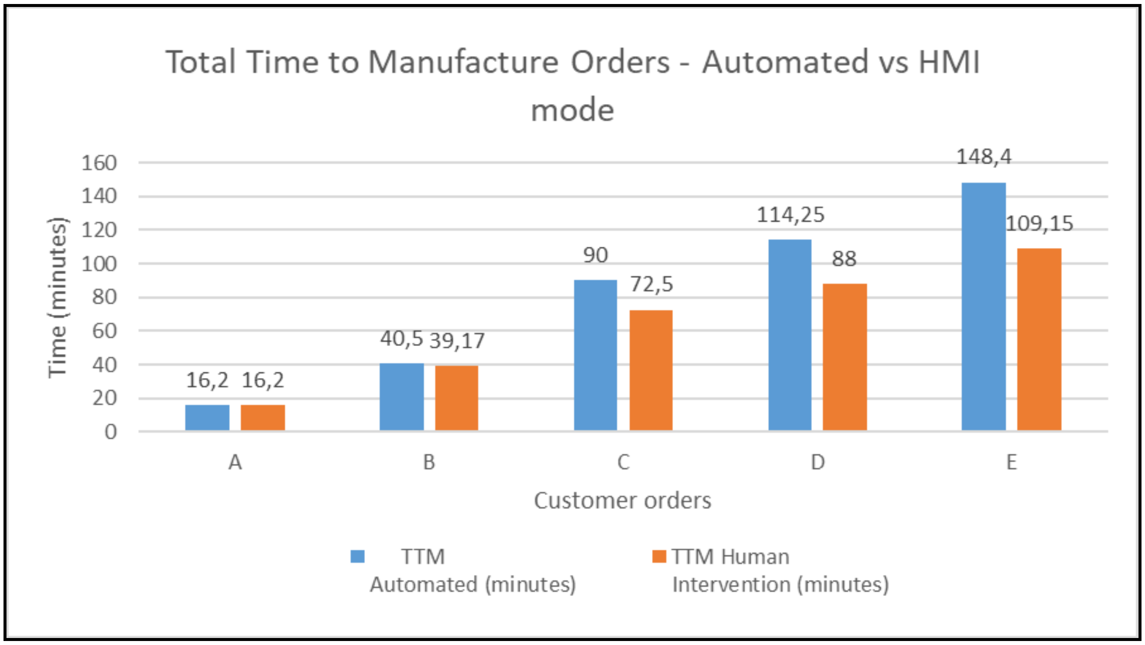
B3 5. The Manufacturing time to complete Scenario 6 customer order: HMI mode

B3: Scenario 6 – TTM for filling and capping customer order: Automated vs HMI mode

B3 6. TTM of customer order for 330ml and 500ml bottles: Automated vs HMI mode – Scenario 5

Customer	Total No of Caps & Bottles	TTM Automated (minutes)	TTM Human Intervention (minutes)	Total Lt used	OEE %	Human Intervention
A	21	16,2	16,2	8,46	100%	No
B	26	40,5	39,17	19,76	96,71%	No
C	28	90	72,5	30,7	80,56%	Yes
D	12	114,25	88	35,51	77,02%	Yes
E	15	148,4	109,15	41,82	73,55%	Yes
TOTAL	102					

As indicated in Table B3.6, the order for Scenario 6 needed a total of 102 bottles and caps to complete. The amount of water used for completing the order was almost 42 liters and as per Table B3.6, the human had to intervene from the order for Customer C as the OEE dropped below 90%. Figure B3.7 illustrates the results found for the TTM of filling and capping the orders in Automated mode vs the HMI mode.



B3 7. Diagram showing the TTM of filling and capping all customer orders for 330ml and 500ml bottles: Automated vs HMI mode - Scenario 6.

Based on the results shown in Table B3.6 and Figure B3.7, one can see that the Total Time to Manufacture for the Automated approach was 148,4 minutes as opposed to the Human-Intervention approach that took a TTM of 109,5 minutes to complete the customer order for Scenario 6.

Appendix C

A list of models based on OEE, listed by the author name and model name as presented by Carmen, et.al [56], is shown in Table 1. A brief description of each model is provided.

Table 4. List of models based on OEE.

Author(s)	Year	Model Name	Brief Description
Huang, S.H.; Dismukes, J.P.; Shi, J.; Su, Q.;Wang, G.; Razzak, M.A.; Robinson, D.E. Muthiah, K.M.N.; Huang, S.H.	2002 2007	Overall throughput	Calculates the productivity of a manufacturing system measures the factory level performance; identifies the bottleneck and hidden capacity.
deRon, A.J.; Rooda, J.E.	2005	Equipment Effectiveness	Measures the equipment-dependent states, such as productive state, scheduled downstate and unscheduled downstate.
Nachiappan, R.M.; Anantharaman, N.	2006	Overall line effectiveness	Measure the productivity of a line manufacturing system
Sheu, D.D.	2006	Total equipment efficiency	To achieve total equipment efficiency, it must include the resource usage efficiency of a machine. This input factor (resource requirements) is known as the overall input efficiency.
Muchiri, P.; Pintelon, L.	2008	Overall asset effectiveness Overall production effectiveness	Measures losses due to external and internal factors contributing to overall production/asset effectiveness.
Badiger, A.S.; Gandhinathan, R.; Gaitonde, V.N.	2008	Modified OEE	Includes new factor usability; it classifies unplanned downtime events into equipment-related downtime.
Dunn, T.	2008	Overall equipment effectiveness of a manufacturing line	Measures the performances of an automated line in the system.
Elevli, S.; Elevli, B.	2010	OEE for shovel/OEE for trucks	OEE is calculated for mining equipment.
Anvari, F.; Edwards, R.; Starr, A.	2010	Overall equipment effectiveness market-based	Monitors production in the steel market; measures equipment effectiveness for a full process cycle.
Raja, P.N.; Kannan, S.M.; Jeyabalan, V.	2010	Overall line effectiveness	The performance of the production line in the manufacturing system is measured.
Anvari, F.; Edwards, R.	2011	Integrated equipment effectiveness	This integration is based on three elements: loading-based, capital-based and market-based elements.
Wudhikarn, R.	2012	Overall equipment and quality cost loss	Calculates the losses of equipment, specifically production and quality cost losses, in monetary units.
Eswaramurthi, K.G.; Mohanram, P.V.	2013	Overall resource effectiveness	Includes losses related to resources, e.g., people, machines, materials and methods.

Jauregui Becker, J.M.; Borst, J.; van der Veen, A.	2015	Machining equipment effectiveness	Calculates the OEE of a high-mix-low-volume manufacturing environment.
Garza-Reyes, J.A.	2015	Overall resource effectiveness	Provides information regarding the process performance based on factor material efficiencies, process cost and material cost.
Domingo, R.; Aguado, S.	2015	Overall environmental equipment effectiveness	Identifies losses due to sustainability, based on the calculated environmental impact of the workstation.
Zammori, F.	2015	Fuzzy overall equipment effectiveness	Identifies performance fluctuations through LR Fuzzy numbers.
Dindarloo, S.R.; Siami-Irdemoosa, E.; Frimpong, S.	2016	Stochastic shovel effectiveness	Quantifies performance effectiveness of electric and hydraulic shovels.
Mohammadi, M.; Rai, P.; Gupta, S.	2017	OEE of BELT equipment	Bucket-based excavating, loading and transport (BELT) including all equipment comprising a bucket, e.g., draglines, shovels, load-haul-dumps and trucks.
Larrañaga Lesaca, J.M.; Zulueta Guerrero, E.; Lopez-Guede, J.M.; Ramos-Hernanz, J.; Larrañaga Juaristi, A.; Akizu, O.	2017	Strategic equipment effectivenessOperational equipment effectiveness	A global measure of the e activeness of an integratedelectrical system.
da Silva, A.F.; Marins, F.A.S.; Tamura, P.M.; Dias, E.X.	2017	Overall machinery effectiveness	Identifies and ranks decision-making-units in terms of efficiency
Pinto, M.M.O.; Goldberg, D.J.K Cardoso, J.S.L.	2017	OEE of port terminal	Identifies the most efficient terminal, addressing either manageable or unmanageable factors.
Puvanasvaran, A.P.;Yoong, S.S.; Tay, C.C.	2017	Modified OEE	Includes losses associated with human factors and usability (the frequency of setup and changeover process)
Nakhla, M.	2018	Extended overall equipment effectiveness	Evaluates the entire process considering human resources and equipment Performance. It is applied in medicals activities of operating rooms.
García-Arca, J.; Prado-Prado, J.C.; Fernández-González, A.J.	2018	OEE to transport management	Improves efficiency in road transport by adapting OEE to transport management.
Muñoz-Villamizar, A.; Santos, J. Montoya-Torres, J.; Jaca, C.	2018	Modified OEE	Optimizes the effectiveness of urban freight transportation.
Braglia, M.; Castellano, D.; Frosolini, M.; Gallo, M.	2018	Overall material usage effectiveness	Measures material usage effectiveness and identifies material loss in the manufacturing process.
Durán, O.; Capaldo, A.; Duran Acevedo, P.	2018	Sustainable overall throughput ability effectiveness	Includes sustainability criteria and can be used in the system lifecycle.
Braglia, M.; Gabbrielli, R.; Marrazzini, L.	2019	Overall task effectiveness	Analyses and evaluates losses related to manual assembly tasks.
Abdelbar, K.M.; Bouami, D.; Elfezazi, S.	2019	OEE-TCQ	Improves the process approach in maintenance in terms of time, cost and quality.
Brodny, J.; Tutak, M.	2019	Overall effectiveness indicator	Adapted for mining production to examine the effectiveness of the mining machine.

Tang, H.	2019	Standalone OEE	Identifies system bottleneck and excludes effects from upstream and downstream.
Durga Prasad, N.V.P.R.; Radhakrishna, C.	2019	Overall substation effectiveness	Measures substation performances and indicates the overall maintenance performances.

As presented above by Carmen, et. al [73], the OEE was adapted to resolve gaps in various matters, such as sustainability, human factor, transport, manufacturing system, mining, cost, port and resources.

Appendix D

As referred to in Section 3.3.1 an OEE score of 85% is considered world class for various manufacturers [58]. However, in this study an OEE score of 90% was adapted to determine where the machine must complete the process in fully automated mode or when human intervention is needed for completion of the process. The following tables and figures showcases the results after executing the experiments when an OEE score of 85% is implemented. The exact same set of customer orders were used as input to SAS to determine the effect on the results of where the machine should complete the process and where human intervention is needed when the OEE score is 85%. The results of Scenarios 1 – 6 are shown in this appendix.

D1: Results for Scenario 1 with 85% OEE score

Based on the results for Scenario 1 with an OEE score of 85% is, it can be seen that the output is the same as when the OEE score of 90% is implemented for Scenario 1. The OEE score is well above 85% in this scenario, thus the machine completes the order without any human intervention as detectable in Table D1.

Table D1. TTM of Automated mode vs HMI mode – Scenario 1(OEE = 85%)

Customer	Total no of Bottles	TTM Automated (minutes)	TTM Human Intervention (minutes)	Total Lt used	OEE %	Human to Intervene
A	18	13,95	13,95	7,47	100%	No
B	9	20,9	20,9	11,12	100%	No
C	13	31	31	16,6	100%	No
D	8	38,5	38,08	20,09	98,91%	No
E	6	46,1	44,02	22,04	95,49%	No
Totals	54	46,1	44,02			

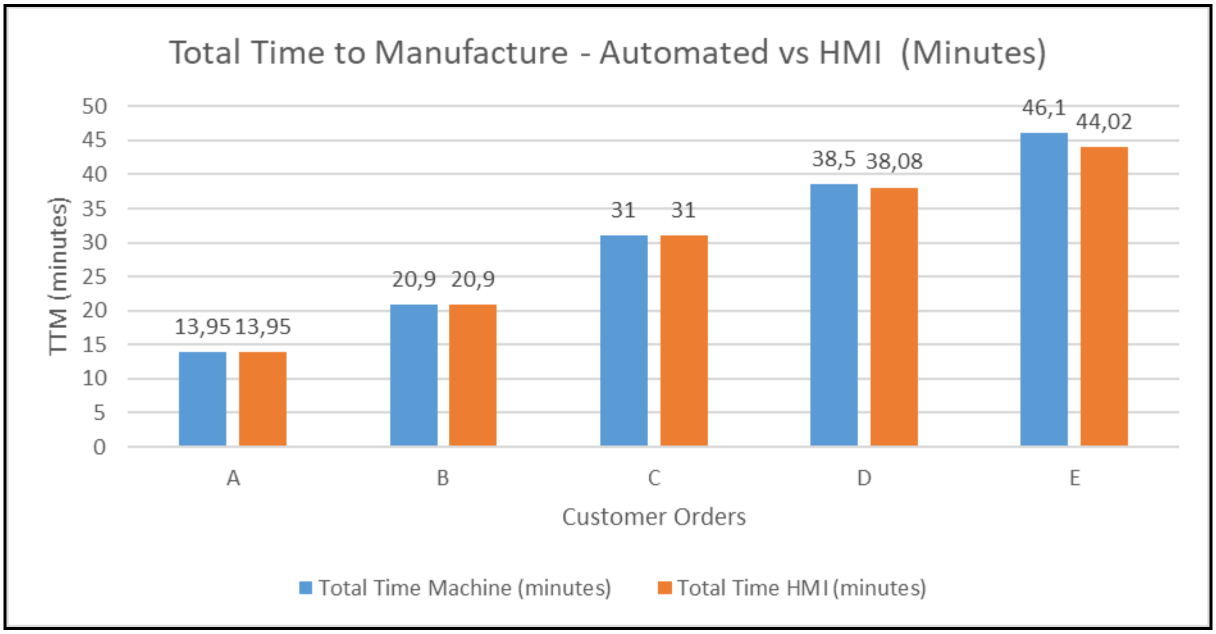


Figure 1. Results of the TTM for Automated mode vs HMI mode – Scenario 1 (OEE = 85%)

D2: Results for Scenario 2 with 85% OEE score

The results of implementing a 85% OEE score is shown in Table D2. Customer order C has an OEE score of 87,74% which allows the machine to complete the order without human intervention as opposed to the results of Scenario 2 in Section 4.4.5, where Customer order C requires human intervention.

Table D2. TTM of Automated mode vs HMI mode – Scenario 2 (OEE = 85%)

Customer	Total No of bottles	TTM Automated (minutes)	TTM Human Intervention (minutes)	Total Lt used	OEE %	Human to Intervene
A	28	21,75	21,75	11,79	100%	No
B	20	40,35	39,35	20,43	97,52%	No
C	21	72,65	63,74	29,23	87,74%	No
D	15	103	83,34	35,37	80,91%	Yes
E	15	137	103,59	41,17	75,61%	Yes
Total no of bottles	99	137	103,59			

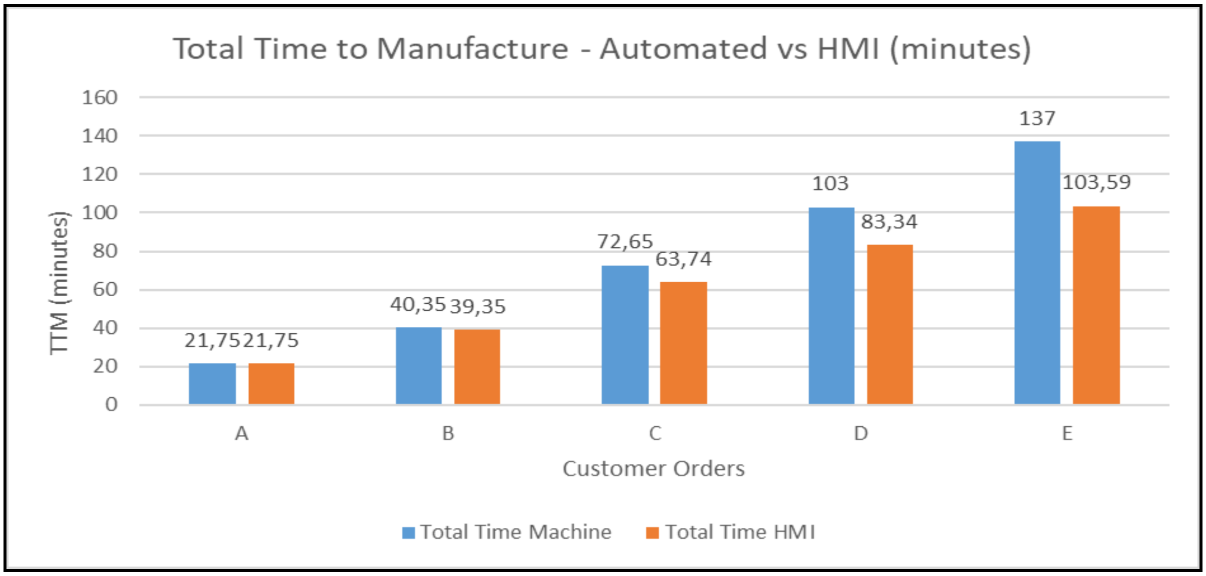


Figure D2. Results of the TTM for Automated mode vs HMI mode – Scenario 1 (OEE = 85%)

Implementing an OEE score of 85% has no effect on the TTM's of the order as can be seen in Figure D2 when compared with Figure 4.6 in Section 4.4.5.

D3: Results for Scenario 3 with 85% OEE score

The results of implementing a 85% OEE score is shown in Table D3. Customer order B has an OEE score of 85,05% which indicates that the machine will complete the order without human intervention as opposed to the results of Scenario 3 in Section 4.5.4, where Customer order B requires human intervention when the OEE score is 90%.

Table D3. TTM of Automated mode vs HMI mode – Scenario 3 (OEE = 85%)

Customer	Total No of Bottles	TTM Automated (minutes)	TTM Human Intervention (minutes)	Total Lt used	OEE %	Human Intervention
A	34	33,3	31,13	15,64	93,48%	No
B	33	84,3	71,71	30,78	85,06%	No
C	25	135,5	106,66	42,26	78,71%	Yes
D	19	177,4	133,81	50,74	75,43%	Yes
E	19	220,2	162,11	59,73	73,61%	Yes
Total no of bottles	130					

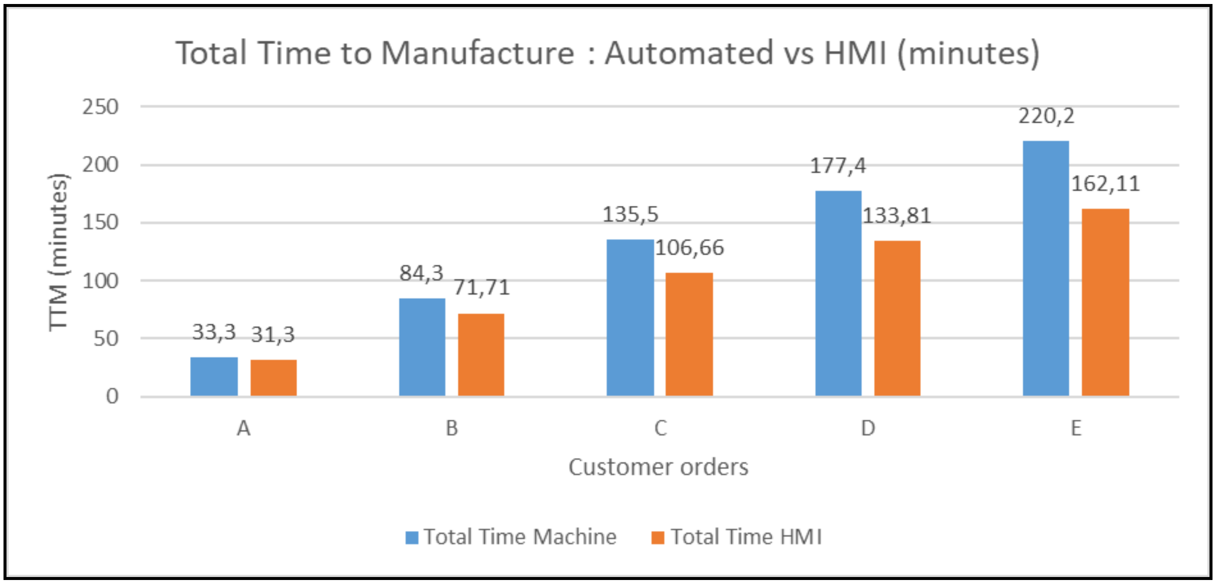


Figure D3. Results of the TTM for Automated mode vs HMI mode – Scenario 1 (OEE = 85%)

D4: Results for Scenario 4 with 85% OEE score

Based on the results for Scenario 4 with an OEE score of 85% is, it can be seen that the output is the same as when the OEE score of 90% is implemented for Scenario 1 in Section 4.6.1. The OEE score is well above 85% in this scenario, thus the machine completes the order without any human intervention as detectable in Table D1.

Table D4. TTM for filling and capping: Automated vs HMI – Scenario 4 (OEE = 85%)

Customer	Total No of Caps & Bottles	TTM Automated (minutes)	TTM Human Intervention (minutes)	Total Lt used	OEE %	Human Intervention
A	10	7,6	7,6	3,64	100%	No
B	11	16,3	16,3	8,8	100%	No
C	5	20,2	20,2	10,96	100%	No
D	4	23,25	23,25	12,45	100%	No
E	9	30,2	30,2	16,1	100%	No
TOTAL	39	30,2	30,2			

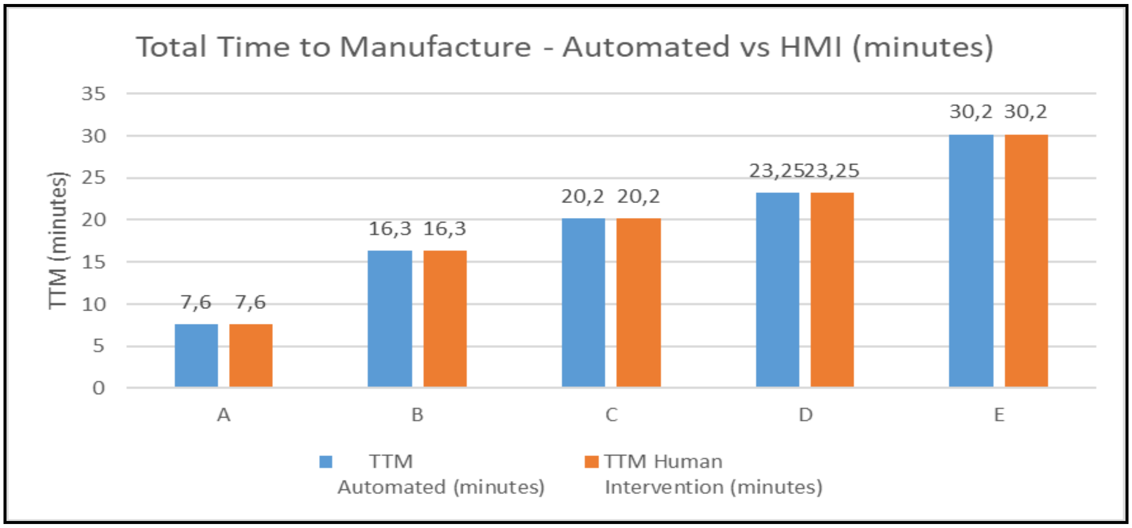


Figure D11. TTM for filling and capping: Automated mode vs HMI mode - Scenario 4. (OEE = 85%)

D5: Results for Scenario 5 with 85% OEE score

The results obtained for executing Scenario 5 with an OEE score of 85% is presented in Table D5. When the results are compared to the results of Scenario 5 in Section 4.6.2, it indicates that the machine will complete the Customer orders A and B without any human intervention. The results are the same irrespective of whether the OEE is 90% or 85%.

Table D5. TTM of customer order for the 330ml and 500ml bottles: Automated vs HMI mode – Scenario 5. (OEE = 85%)

Customer	Total no of caps and bottles	TTM Automated (minutes)	TTM Human Intervention (minutes)	Total Lt used	OEE%	Human Intervention
A	13	21,75	21,75	11,79	100%	No
B	31	55,35	50,35	23,73	90,97%	No
C	38	90,15	74,06	31,54	82,15%	Yes
D	41	110,5	87,83	36,03	79,48%	Yes
E	45	130	100,25	39,85	77,11%	Yes
TOTAL	95	130	100,25			

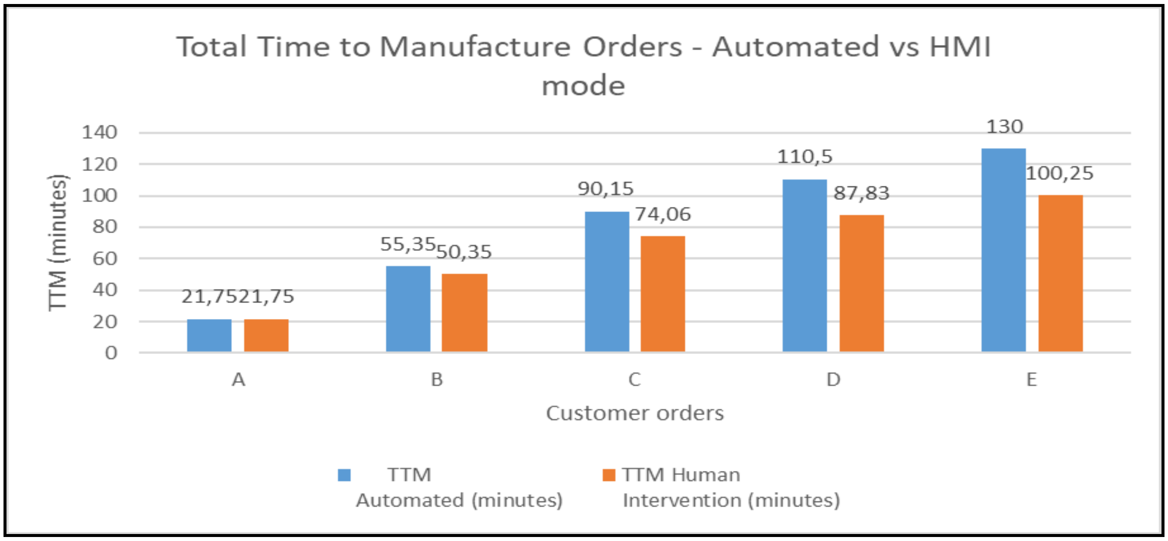


Figure D5. Diagram showing the TTM of filling and capping all customer orders for 330ml and 500ml bottles: Automated vs HMI mode - Scenario 5 (OEE = 85%).

D6: Results for Scenario 6 with 85% OEE score

By comparing the results of Scenario 6 in Section 4.6.3 with the results in Table D6 below, it shows that the results are the same regardless of whether the OEE is 90% or 85%.

Table D6. TTM of customer order for the 330ml and 500ml bottles: Automated vs HMI mode – Scenario 6 (OEE = 85%).

Customer	Total No of Caps & Bottles	TTM Automated (minutes)	TTM Human Intervention (minutes)	Total Lt used	OEE%	Human Intervention
A	21	16,2	16,2	8,46	100%	No
B	26	40,5	39,17	19,76	96,71%	No
C	28	90	73,83	30,7	80,56%	Yes
D	12	114,25	105,5	35,51	77,02%	Yes
E	15	148,4	135,4	41,82	73,55%	Yes
TOTAL	102	148,4	135,4			

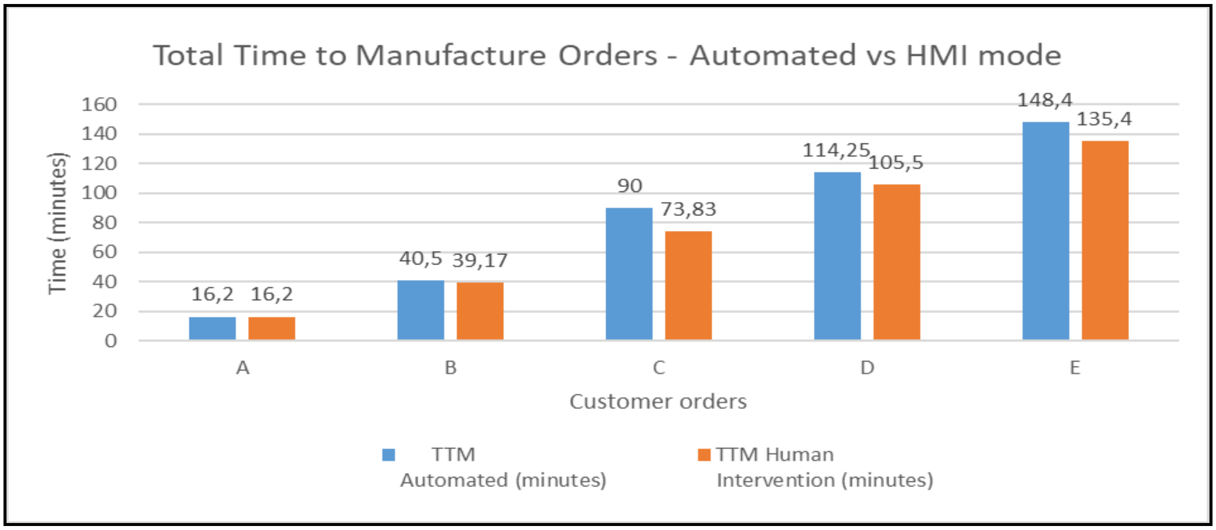


Figure D6. Diagram showing the TTM of filling and capping all customer orders for 330ml and 500ml bottles: Automated vs HMI mode - Scenario 6 (OEE = 85%).

Appendix E

Pictures of the physical setup of the water bottling plant.

Figure E.1. The water bottling plant in operation.

Figure E.2. A water bottle being filled at SMU1.

Figure E.3. A water bottle being capped at SMU2.

Figure E.4. The production process of the water bottling plant..