Designing a Digital Twin for a Mixed Model Stochastic Assembly Line for the Reduction of Cycle Time

by

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Declaration of Independent Work

I, PHILANE TSHABALALA, student number __________, do hereby declare that this research project submitted to the Central University of Technology, Free State, for the Degree MASTER OF ENGINEERING: ELECTRICAL ENGINEERING, 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; and has not been submitted before to any institution by myself or any other person in fulfilment (or partial fulfilment) of the requirements for the attainment of any qualification.

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SIGNATURE OF STUDENT DATE

Dedication

To my family and friends, for their support and prayers to me, always.

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Abstract

The shift from traditional manufacturing techniques to the fourth industrial revolution era has brought about significant changes to the manufacturing landscape. One such noticeable change is the shift from mass production to customised production. This shift has emanated from the demand for product variety in today's market, implying that assembly lines, which are the backbone of a production line, must now be re-designed to produce multiple variants of a product. However, this accentuates the system's complexity and has therefore created a need for a system that can perform real-time monitoring and fault-finding in order to avoid the bottlenecks that are caused by an increased cycle time. Cycle time is a key factor in assembly line balancing, as it influences efficiency and cost of an assembly line and as such cycle time reduction is seen as a critical element in the optimised operation of an assembly line. Currently, most of the techniques used for cycle time reduction in an assembly line revolve around heuristics approaches and simulation-based techniques. The drawback of these approaches, as postulated in the literature, is that there is limited research on using real-time data as inputs, and they are mostly only suitable for a limited set of inputs. This is not suited for the stochastic nature of the modern-day assembly line. The industry 4.0 era has brought about many new strategies to ensure that production processes are customised to satisfy individual customer demands. Among the new strategies developed to improve production efficiency in the manufacturing arena is the digital transformation of the manufacturing line. Two of the popular tools that are used for implementing this digital transformation are Digital Twins (DTs) and Digital Shadows (DSs). Unlike heuristics and simulation-based techniques, DTs can utilise real-time data as inputs and therefore provide real-time visualisation and prediction of several what-if scenarios. This research looks at the design of a real-time data-driven Digital Twin (using MATLAB/SIMULINK) for a Mixed Model Assembly Line Balancing Problem (MALBP), with focus on cycle time reduction. A case study of a water bottling plant operating at the Central University of Technology (CUT) capable of producing multiple variants of water bottles will be used in this research. The Digital Twin will be synchronised with the plant for real-time monitoring of the process flow with the aim of reducing the cycle time and optimising production. The results of this research study highlight the impact of real-time data and using Digital Twins in a Mixed Model Stochastic Straight-type Assembly Line, with the cycle time reduced by 19% on average, compared to when using the Digital Shadow.

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Chapter 1: Introduction to Study Environment

1.1 Introduction

Prior to the Fourth Industrial Revolution (henceforth referred to as Industry 4.0), manufacturing industries focused on producing products in volume ahead of the customer demand and kept them in stock until they were ready to be shipped once an order is processed. This manufacturing strategy is referred to as the Make-To-Stock (MTS) approach [1]. Some of the disadvantages of this strategy, but not limited to these, are that there is less variety in the products, loss of capital if the number of products produced is higher than the demand, and the associated risk if the products produced have a shorter lifespan [2].

The advent of Industry 4.0 has shifted the focus from mass production to customised production. This shift is in order to keep up with the continuous improvements and the competitiveness of the current global market [3]. Unlike in the MTS mode, Make-To-Order (MTO) is a manufacturing strategy that enables product variety, as in this approach the production orders are not predictable and production only initiates after the customer's order is placed and received, reducing the exposure to financial risk [2].

The increased product variety that comes with the MTO approach and the fact that MTO systems are stochastic in nature means that assembly lines must be designed in a way that they meet the demands of product variety [4]. The assembly lines that are major enablers to handle product variety are Mixed Model Assembly Lines (MMALs) [5]. MMALs can assemble different products on the same assembly line without any changes to the sequencing of these products [6]; as a result, more and more industries now opt for MMALs to meet the demands of the current market.

However, there are some challenges that comes with using MMALs for product variety, which increase complexity and therefore bear a negative impact on productivity and quality [7]. Two of the common challenges are line balancing and sequencing, with line balancing being considered a long-term planning problem and sequencing being a considered short-term [8]. This research focuses on line balancing.

The Mixed-Model Assembly Line Balancing Problem (MALBP) occurs during the design stages of mixed-model assembly lines, and it can be defined as the assignment of assembly tasks to different workstations in the production line to level workload, while satisfying specific constraints [9]. There are two types of MALBPs which are referred to as dual problems, namely: MALBP-I and MALBP-II [10]. In MALBP-I, the focus is on minimising the number of workstations with a given cycle time, and in MALBP-II the focus is on minimising the cycle time with a fixed number of workstations [10].

Workstation reduction, reduced smoothness index, cycle time reduction and lead time reduction are some of the main assembly line balancing objectives [11]. However, this research will only focus on cycle time reduction, implying that the focus of this study is on a type II MALBP.

Cycle time can be defined as the amount of time it takes to convert raw materials into finished products [12]. Cycle time reduction has a positive impact on the productivity, costs and enables faster response to the customer demand [12], thus, longer cycle times mean a decrease in the quality of customer service [13].

Authors [14][15][16] have previously proposed solutions for assembly line balancing problems, however, very few have researched cycle time reduction. The few studies that focused on cycle time reduction used optimal solutions. The limitation of optimal solutions is that they have a limited number of variables and constraints that can be used in the software that solves models; therefore, they cannot solve large-size problems of mixed-model assembly lines [17].

This research therefore proposes a Digital Twin (DT) as a possible solution to the cycle time reduction challenge. A Digital Twin is a virtual copy of a real-world object that is designed to predict, simulate, optimise and control the conditions of this real-world system [18], using the historical data of the system and the live data that comes from the sensors [19]. In this research, a DT will be designed to monitor the process flow in a Mixed-Model Stochastic System in real-time in order to reduce the cycle time and optimise production. An MMSS assembly line is chosen in this research as it is more complex than other assembly line systems.

1.2 Problem Statement

The advent of Industry 4.0 has resulted in the move from the traditional Make-To-Stock (MTS) approach to the Make-To-Order (MTO) approach. The MTO approach adds considerable pressure on an already strained production line. One such challenge is that of increased cycle time. This challenge is accentuated when considering a mixed-model stochastic production line.

1.3 Research Question

How can the manufacturing cycle time of a Mixed-Model Stochastic Straight-type (MMSS) Assembly Line be reduced to increase production efficiency?

1.4 Research Hypothesis and Objectives

1.4.1 Research hypothesis

The design of a real-time data-driven Digital Twin of a physical Mixed-Model Stochastic (MMS) assembly line that will be able to monitor the process flow and reduce cycle time, thereby optimising production.

1.4.2 Research aim

The aim of this research is to design a data-driven Digital Twin of a Mixed-Model Stochastic assembly line for continuous real-time monitoring of the process flow and prediction of bottlenecks in the production line in order to reduce the cycle time and thereby improve efficiency.

1.4.3 Research objectives

The main objectives are as stated:

- Create a software model for a Mixed-Model Stochastic assembly line. This model will function as a Digital Shadow.

- Install and integrate sensors to the Mixed-Model Stochastic assembly line and use the real-time data from the sensors as inputs to the Digital Shadow model, thereby converting the Digital Shadow model into a Digital Twin.

- Analyse and compare the value of cycle time calculated by the Digital Shadow and the Digital Twin for a similar production process and establish the advantage of the Digital Twin.

1.5 Research Methodology

This research will be conducted using the case study of the Make-to-Order (MTO) water bottling plant at the Central University of Technology, Free State (Bloemfontein campus). The MTO water bottling plant is made up of three Smart Manufacturing Units (SMUs) for filling, capping and packaging. The plant produces two variants of water bottles (330ml and 500ml). The methodology deployed in this research study is summarised as follows:

- Design Digital Shadow model for the water bottling plant using MATLAB/SIMULINK. This model will use the customer orders as inputs to run tests and simulations in order to calculate the cycle time.

- Integrate sensors to convert the Digital Shadow into a Digital Twin. This will be accomplished by installing the following Internet of Things (IoT) sensors; Ultrasonic sensor (for water level), flow meter, infrared sensor(s) for 330ml and 500ml water bottles to the different SMUs of the plant and using the live data from the sensors, the Digital Shadow model will now be converted into a Digital Twin model. The live data from these sensors will be brought to the Digital Twin on MATLAB/SIMULINK through *ThingSpeak* (a cloud server) for real-time monitoring, simulation and to calculate the cycle time.

- Analyse and compare the performance of the Digital Shadow model and the Digital Twin model based on the cycle time calculations. This will be accomplished by providing a similar set of customer orders as inputs to the Digital Shadow as well as the Digital Twin.

1.6 Dissertation Layout

Chapter 1: Chapter 1 is the introduction to the research; the background information and current operation of the manufacturing sector is partially discussed in this chapter. This chapter also introduces aspects such as the problem statement, hypothesis, research objectives and research methodology.

Chapter 2: Chapter 2 details the literature review that was conducted prior to this study. This chapter firstly provides an overview on different types of assembly lines, along with their classifications. It then discusses the assembly line balancing problems. Next, the factors affecting the production time, with focus to cycle time, is explored. The different techniques that are currently used to reduce cycle time in assembly line balancing are also discussed in this chapter. The chapter is concluded with an overview on the limitations of existing research.

Chapter 3: Chapter 3 reviews the research methodology that was undertaken in this study. The chapter first highlights the importance of the selected case study, in support to the study. Next, the chapter details the design and development of the Digital Shadow model and the Digital Twin model, both developed using the *MATLAB* and *SIMULINK* platforms to optimise production in the case study.

Chapter 4: Chapter 4 details the cycle time tests that were performed on the Digital Shadow and Digital Twin model, using the customer orders as inputs. Next, a comparison between the results of the models is done, to showcase the model which optimises production more efficiently.

Chapter 5: Chapter 5 discusses the results of the Digital Shadow and Digital Twin models, developed on SIMULINK, and a performance comparison is made between the models and the existing methods. This chapter also answers the questions raised in the problem statement in Chapter 1 and the limitations of existing research elaborated upon in Chapter 2.

Chapter 6: Chapter 6 concludes the study by summarising the work done in this study, highlighting the research goals, recommendations and future works.

Chapter 2: Literature Review

2.1 Introduction

The aim of this chapter is to showcase the detailed literature review that was undertaken prior to this study. This will be used as a guideline in establishing the research gap and familiarising the researcher with the selected research niche. This chapter will discuss the assembly lines, assembly line classification, and assembly line balancing problems in detail. This chapter will also discuss the different factors that affect the production time and the techniques that are available and currently used for the reduction of cycle time. Finally, the limitations of existing techniques, which necessitated this study, will be elaborated upon.

2.2 Assembly Lines

An assembly line is a production line that consists of a conveyor belt which carries the product through a series of workstations, from raw materials to a finished product [20]. Assembly lines have been an integral component in the manufacturing industry, since their first design by Henry Ford in the manufacture of the Ford Model T motor vehicles in the early 1900s [21][22], up to the present Industry 4.0 era. The goal of an assembly line is to accelerate the production process and enhance efficiency, while minimising the production time and, thereby, costs [22].

Assembly lines have evolved over the years from their initial design by Henry Ford to become more flexible and autonomous. The evolution in assembly line design was necessitated to keep up with today's market demands and for industries to adapt to the shift from the traditional mass production to customised production that is occurring in Industry 4.0. This implies that there must be a shift from the fixed assembly lines to the flexible ones, mainly to enable product variety [23].

However, opting for more flexible assembly lines to enable product variety has led to more challenges, as this accentuates the already complex process of assigning tasks to the different workstations. This process of grouping tasks into the different assembly line's workstations is referred to as Assembly Line Balancing (ALB). ALB aims to maximise the total production rate [11].

2.2.1 Definitions of related terms

The related terms that are used in assembly line balancing are named and defined in this section for clarity:

- **Assembly line** – An assembly line is a production line made of workstations, where these workstations are linked together by a transportation system known as a conveyor belt for moving products from one station to another [24].

- **Workstation** – A workstation is a station on a production line where certain tasks are performed [25].

- **Task** – A task is a set of work that is performed in a workstation by an operator(s) [24].

- **Line Balancing** – Line balancing is a process that occurs in an assembly line where the workload is levelled across the workstations to reduce the bottlenecks [26].

- **Cycle Time** – Cycle time is the maximum amount of time taken to complete all of the tasks assigned to a workstation before the product can move to the next workstation [27].

- **Lead Time** – Lead time is the total amount of time taken from when a customer is placing an order to when the product is delivered to the customer [28].

- **Bottleneck** – Bottlenecks are delays in the production line that have a negative impact on the production rate. Line balancing is a solution to bottlenecks [29].

- **Smoothness Index** – Smoothness index is the indication of how smoothly a product flows through the production line. The smoothness index must be zero or close to zero for a production line to be classified as a perfect, well-balanced line [22].

2.2.2 Assembly line classification

This section investigates the classification of assembly lines. Figure 2.1 shows some of the most important parameters of the classification of assembly lines.

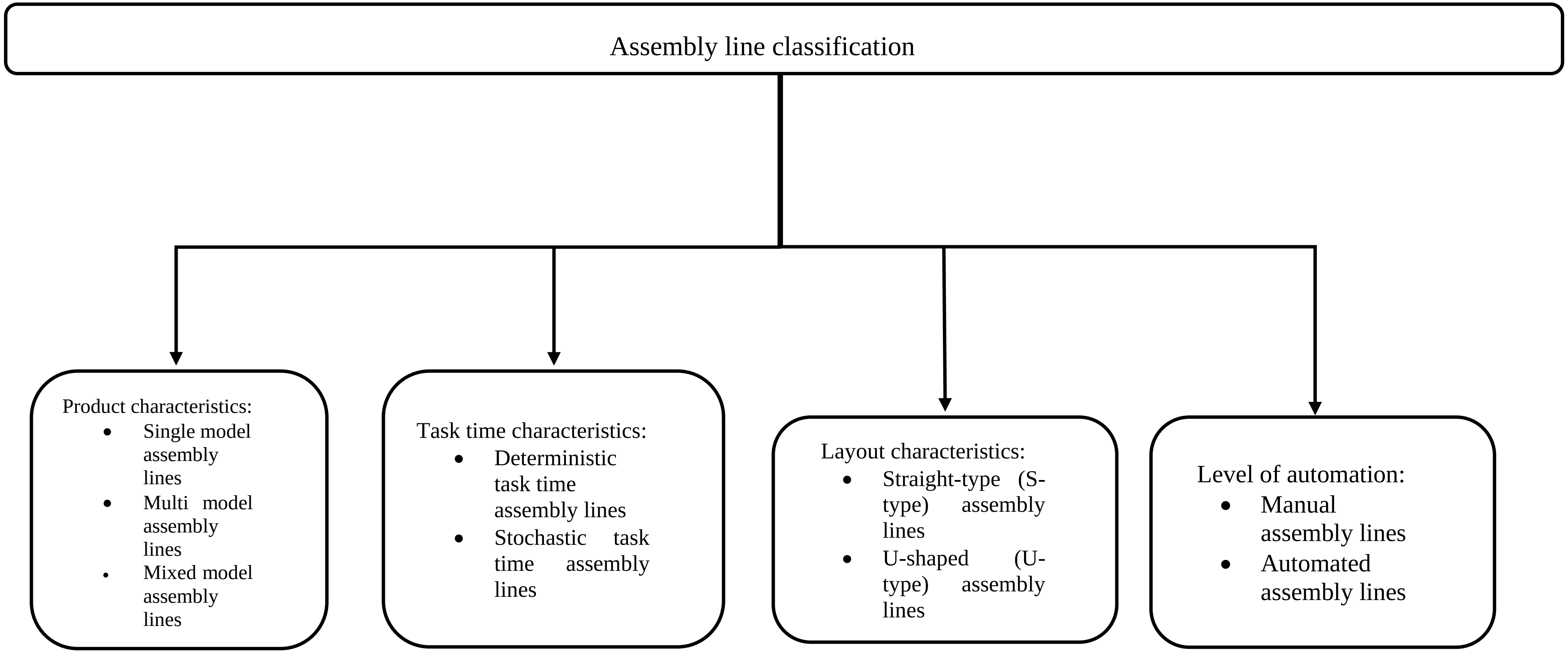

Figure 2.1: Assembly line classification

2.2.2.1 Product characteristics

There are three different types of assembly lines that are used in product assembly. These assembly lines are:

- **Single model assembly lines** – This type of assembly lines are the simplest version of assembly lines, as they produce a large quantity of only a single product at a time [30]. All assembled products are the same in these assembly lines, there are no variations [30].

- **Multi model assembly lines** – This is the type of assembly lines where multiple products are produced and divided into batches [30][31]. These are the most complex assembly lines out of the three assembly lines as, after every batch, some changes must be made on the assembly line; these changes are referred to as changeovers [22].

- **Mixed-model assembly lines** – This type of assembly lines are designed in such a way that they are capable of producing a variety of products at the same time without any changes to the sequencing of these products or any changeovers [32].

2.2.2.2 Task time characteristics

The time at which the tasks are executed in a workstation is referred to as task time [33]. There are two types of task times in assembly lines and selection of the task time depends on the goal that particular assembly line must achieve. The two types of task time are:

- **Deterministic task time assembly lines** – The inputs in this type of assembly lines are known and constant throughout the entire production [34].

- **Stochastic task time assembly lines** – The inputs in this type of assembly lines vary throughout the entire production [34].

2.2.2.3 Layout characteristics

The physical arrangement or setting of the workstations in a production line is referred to as line layout [30]. The two well-known types of line layouts are [35]:

- **Straight-type (also known as the S-type) layout** – The workstations in this type of assembly line are set up in a straight line along the conveyor belt [36]. Workers in the S-type layout perform the tasks allocated to each workstation, standing only on one side of the of the assembly line [36].

- **U-shaped type (also known as the U-type) layout** – As the name implies, in these assembly lines the workstations are set up in a "U-shape". The aim of the U-type layout is to provide flexibility and improve efficiency, while also increasing the functionality, as workers can work on either side of the assembly line [37].

2.2.2.4 Level of automation

The performance of tasks by machines rather than operators in a production system is referred to as automation [38]. The main aim of assembly line automation is to reduce labour costs, errors, and the operator workload in order to optimise production [38]. There two main categories of the level of automation in assembly lines [39]:

- **Manual assembly lines** – These are the type of assembly lines whereby operators are preferred to do majority of the tasks allocated to the multiple workstations of the production system with little or no assistance of machines, for economic reasons [40].

- **Automated assembly lines** – These are the type of assembly lines whereby machines are preferred to do the tasks in the multiple workstations of the production system with little or no assistance from the operators [41].

2.3 Assembly Line Balancing Problems (ALBPs)

Multiple workstations are connected end-to-end to form what is referred to as an assembly line [42]. The tasks must be evenly distributed to these workstations to keep the production efficient, as not doing this will result in bottlenecks [42]. However, there are problems encountered when deciding on how to evenly distribute these tasks to workstations and these problems are referred to as Assembly Line Balancing Problems (ALBPs) [43].

2.3.1 Classification of Assembly Line Balancing Problems

Different kinds of problems are encountered when balancing an assembly [44]. Various researchers have documented the classification of ALBPs. One such classification was proposed by Baybars [31], in which he divides the assembly line balancing problems into two major studies [31], namely: Simple Assembly Line Balancing Problems (SALBP) and Generalised Assembly Line Balancing Problems (GALBP), as shown in Figure 2.2.

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- **SALBP** – This is the most common and the simplest version of ALBPs [45]. The objective in these type of assembly lines is to minimise the number of workstations for a fixed cycle time and vice versa [45]. The simple assembly line balancing is usually preferred when the line is required to produce the same type of product [46].

- **GALBP** – The problems that are not included in SALBP are considered as GALBP [45]. The GALBPs are Mixed-Model Assembly Line Balancing Problem (MALBP), Mixed-Model Sequencing Problem (MSP), and U-shaped Assembly Line Balancing Problem (UALBP) [47].

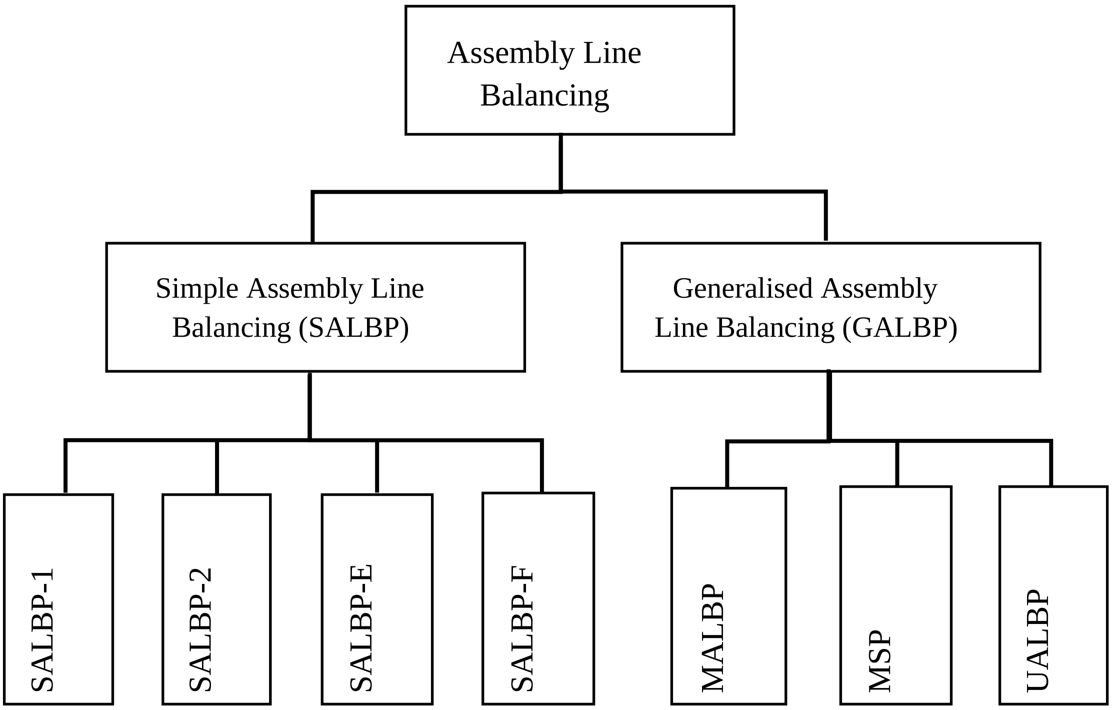

Figure 2.2: Classification of ALBPs according to Boysen, Fliender and Scholl [47]

The SALBP can be split into the following four groups [48]:

- **SALBP-1 (Type-1)** – The objective of type-1 is to group tasks in a way that the number of workstations is minimised for a fixed cycle time [49].

- **SALBP-2 (Type-2)** – The objective of type-2 is to group tasks in a way that the cycle time is minimised for a fixed number of workstations [50].

- **SALBP-E (Type-E)** – The objective of type-E is to minimise both cycle time and number of workstations, while maximising the efficiency (E) of the production line [50].

- **SALBP-F (Type-F)** – The objective of type-F is to determine the feasible line for a combination of the number of workstations and cycle time [49].

The GALBP can be split into the following three groups [49]:

- **MALBP** – Looks at problems that arises in mixed-model assembly lines [51].
- **MSP** – Looks at the sequencing problems in mixed-model assembly lines and needs to find a sequence for all the products to be produced, in a way that ensures work overloads, line stoppages and off-line repairs are minimised [52].
- **UALBP** – Looks at the problems in U-shaped assembly lines, where the workstations are arranged in a U-shape and workers can work on either side of the U. Therefore, the modification in precedence needs to be observed [53].

Eghtesadifard *et al.* [54] progressed on this ALBP classification research, taking a different direction, considering product variety (looking at single model and multi/mixed-model assembly lines), task times and the line layout. The proposed classification by Eghtesadifard *et al*. is shown in Figure 2.3:

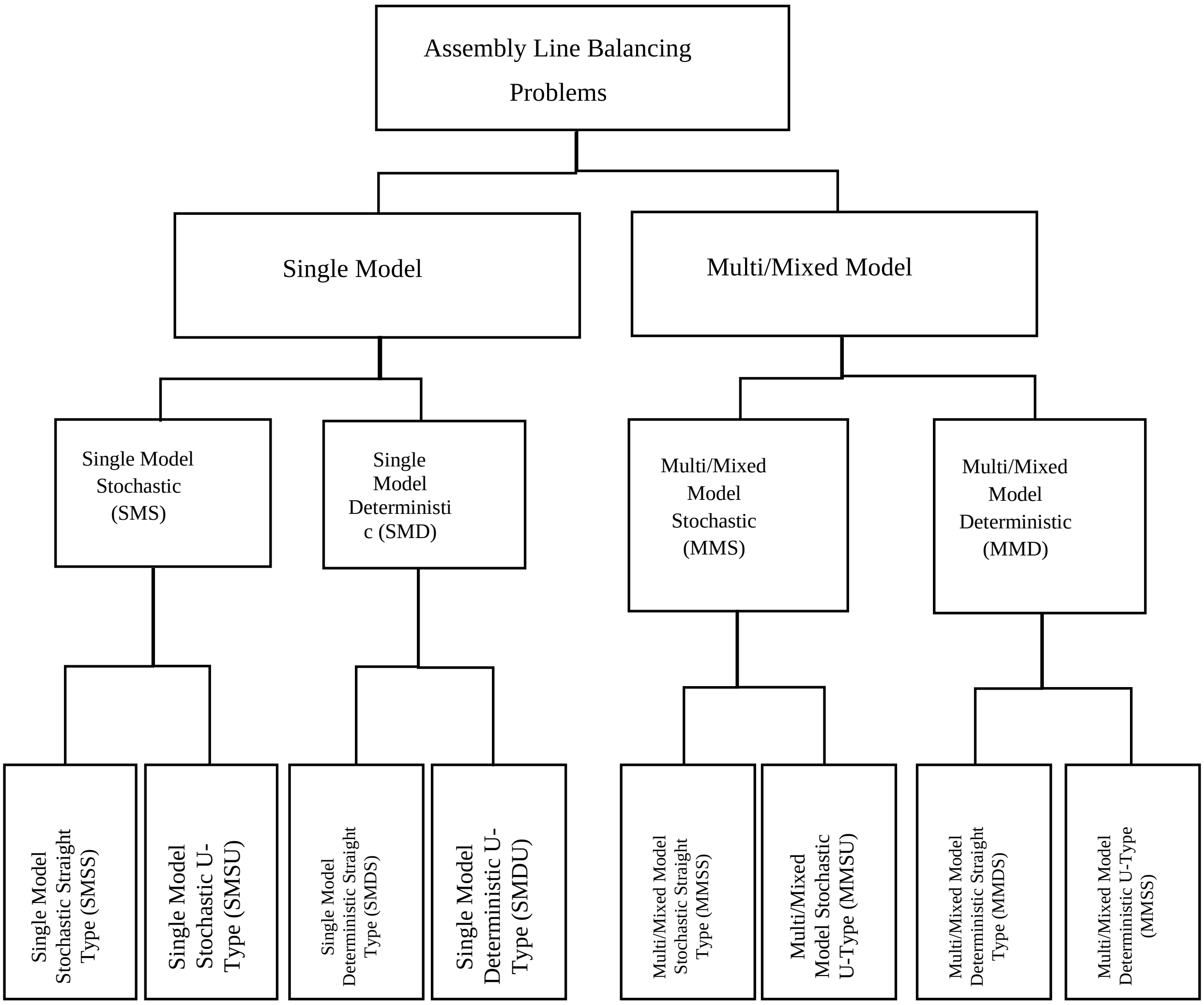

Figure 2.3: ALBPs classification by Eghtesadifard et al. [54]

- **Single Model Deterministic Straight Type (SMDS)** – The SMDS type is the easiest and simplest out of all the assembly line balancing problems. This type focuses on assembly lines whereby only a single model is manufactured, and the workstations are arranged in a straight line, with a deterministic task time in each workstation.

- **Single Model Deterministic U-Type (SMDU)** – The SMDU type focuses on assembly lines whereby only a single model is manufactured, and the workstations are arranged in a U-shape layout, with a deterministic task time in each workstation.

- **Single Model Stochastic Straight Type (SMSS)** – The SMSS type is similar to the SMDS and SMDU types in the way that it also focuses on assembly lines whereby only a single model is manufactured. The difference is that the task time in each workstation is stochastic in this type, and workstations are arranged in a straight line.

- **Single Model Stochastic U-Type (SMSU)** – The SMSU type is similar to the SMSS. The difference is that in this type, the workstations are arranged in a U-shape, with a stochastic task time for each workstation.

- **Multi/Mixed-Model Deterministic Straight Type (MMDS)** – The MMDS type focuses on assembly lines whereby multiple models are manufactured. Even though the workstations are arranged in a straight line with a deterministic task time like in SMDS, the fact that multiple models are manufactured in MMDS increases its complexity much more compared to the SMDS.

- **Multi/Mixed-Model Deterministic U-Type (MMDU)** – The MMDU is similar to the MMDS in that they both focus on assembly lines whereby multiple models are manufactured. The difference is that in MMDU the workstations are arranged in a U-shape, with a deterministic task time in each workstation.

- **Multi/Mixed-Model Stochastic Straight Type (MMSS)** – The MMSS is similar to the MMDS and MMDU types in that it focuses on assembly lines whereby multiple models are manufactured. The difference is that the workstations are arranged in a straight line and the task time in each workstation is stochastic. It should be noted that the MMSS is much more complex than the SMSS.

- **Multi/Mixed-Model Stochastic U-Type (MMSU)** – The MMSU is considered the most complex out of the already mentioned eight types, as it focuses on assembly lines whereby multiple models are manufactured in a line where workstations are arranged in a U-shape with each workstation having a stochastic task time.

2.3.2 Summary of Assembly Line Balancing Problems and Solution Methods

This section summarises the studies done on various assembly line balancing problems discussed in Section 2.3.1. This done by, firstly, tabulating the number of recorded studies with respect to the assembly line balancing techniques, as shown in Table 2.1. Secondly, the table is analysed for better understanding of the most common assembly line balancing problems and the suitable techniques.

Table 2.1: Number of studies done on assembly line balancing problems with respect to the balancing methods

	SMDS	SMDU	SMSS	SMSU	MMDS	MMDU	MMSS	MMSU
Mathematical Modelling	9		4		5		1	
Heuristics	13	2	3	1		2		
Ant Colony Optimisation	7	3			2		1	1
Genetic Algorithm	15		4	1	7	3	1	1
Simulated Annealing	5	1	2		2			1
Tabu Search	4			1	1			
Petri Net	2							
Lean Manufacturing					1	1		
Digital Shadows	1				1			
Digital Twins	1				1			
Total	57	6	13	3	20	6	3	3

A graphical representation of Table 2.1 depicts that, at the time of writing this thesis, there were no studies done on Mixed/Multi-Model Stochastic Straight-type (MMSS) assembly lines along with the Mixed/Multi-Model Stochastic U-type (MMSU) assembly lines using Digital Twins as a balancing technique with the aim to reduce the cycle time. This is depicted in Figure 2.4.

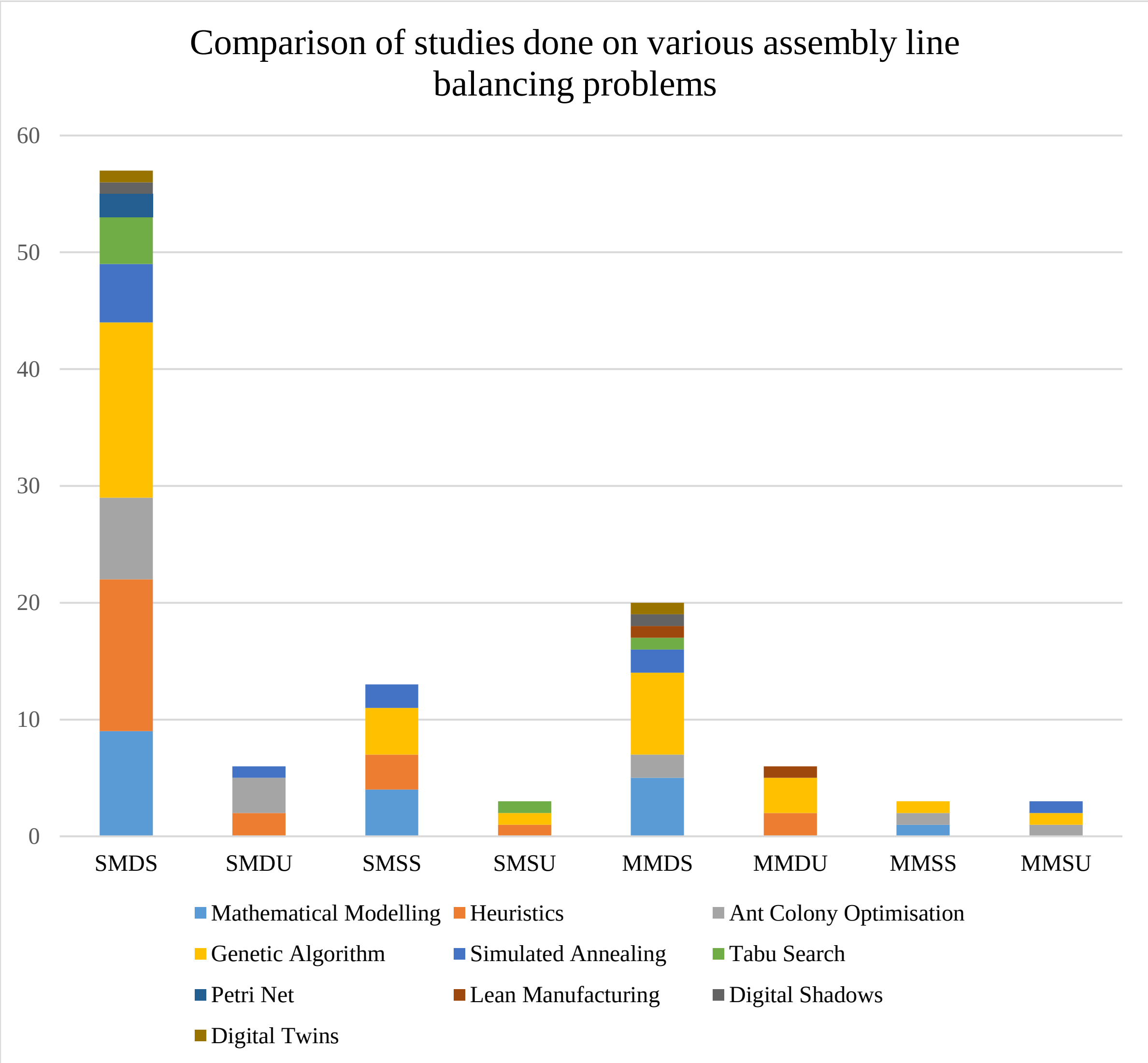

Figure 2.4: Comparison of studies done on various assembly line balancing problems

It can also be observed in Figure 2.4 that the Mixed/Multi-Model Stochastic Straight and U-type assembly lines are the least researched along with the Single Model Stochastic U-type assembly lines. Another graph depicts that, owing to the novelty of Digital Twins and Digital Shadows, there is very little research done using Digital Shadows and Digital Twins as a solution to line balancing problems, as compared to meta-heuristics methods such as Genetic Algorithms and heuristics along with mathematical modelling techniques. This is depicted in Figure 2.5.

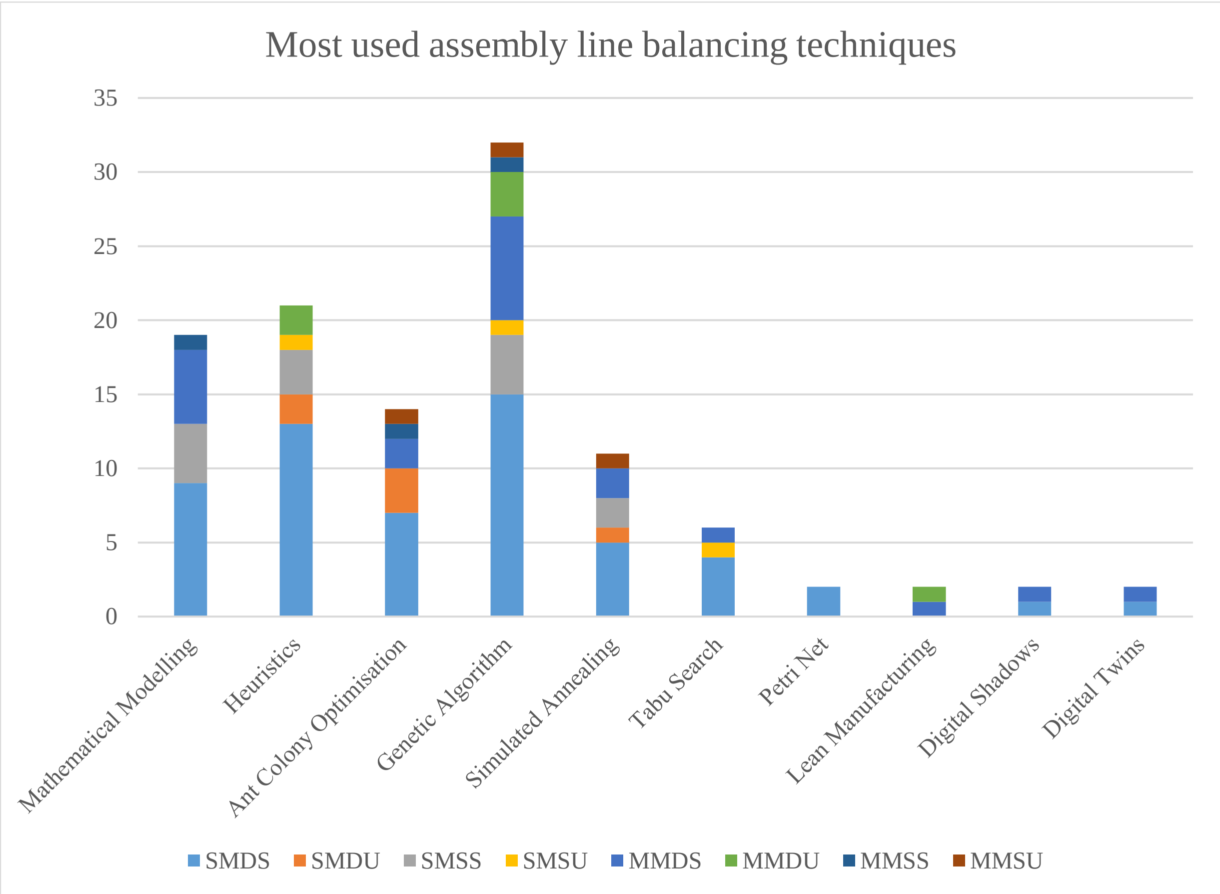

Figure 2.5: Commonly used assembly line balancing techniques

2.4 Factors Affecting the Production Time

This section looks at some of the factors that affect the production time in the manufacturing set. These factors are:

- **Number of Workstations** – In the early 1900s, Hendry Ford introduced the first assembly line [55]. The aim of the designed assembly line was to make the way of manufacturing a certain product efficient and highly productive [56]. A basic assembly line is made up of workstations connected end-to-end in a straight-line layout [56], with products moving from one workstation to the next [57]. A workstation can be defined as any point in the assembly line where a product stops, and certain tasks are performed on the product [58]. The reduction of the workstations is playing a significant role in improving production efficiency [59], as reducing the number of workstations will have a positive impact on both the space requirements and labour costs, provided that constraints such as cycle time, precedence and the production rate are known [58].

- **Lead Time** – Lead time plays an important role in the planning and execution of customer orders, as it has a huge impact on the inventory costs and customer service [60]. Lead time can be defined as the time it takes to complete a single order, from the placement of the order to the order being received by the customer [61]. Continuously reducing the lead time can have tremendous benefits, some of these benefits being improved productivity which will result in the company being able to compete in the current global market [62], as increased lead time will have a negative impact on the production time, resulting in poor customer service [62].

- **Smoothness Index** – This is one of the optimisation methods that are used in line balancing [63]. However, smoothness index is an index that defines the relative smoothness of operation of an assembly line [64]. The smoothness of a perfectly balanced line should be equal to or close to 0, as the lower the value of the smoothness index, the better the assembly line [65][64].

- **Bottlenecks** – Bottlenecks are delays in the manufacturing process that slow down production and therefore result in an increased production time which, in turn, causes late deliveries [66]. One of the ways to optimised production, is the identification and clearing of bottlenecks in the production system [67], as this will keep the production of the system efficient.

- **Cycle Time** – Cycle time in manufacturing refers to the sum of all the processing and waiting times that are required to turn raw materials into a complete product [68]. The demand for manufacturing firms to respond more quickly by customers has increased since the advent of Industry 4.0 [69], hence, the shift from make-to-stock to make-to-order. This has made reduction of cycle time one of the most important elements in the manufacturing process when a company is trying to improve productivity and hasten the customer response [70]. One of the ways to reduce cycle time is by clearing the bottlenecks in the production process [70]. Net Production Time is the time taken from the beginning of the production to the end of production, dividing the Net production time with the number of products produce results into the cycle time. The expression to calculate cycle time:

$$Cycle\ Time\ (CT) = \frac{Net\ Production\ Time}{Number\ of\ Units\ Produced}$$

These factors all have a significant impact on the production time. However, this research will only focus on the reduction of cycle time, as reducing cycle time means taking into consideration the number of workstations, the lead time (reduced cycle time means reduced lead time), the smoothness index and the minimisation of bottlenecks, therefore minimising labour costs and optimising production.

2.5 Techniques that are Currently used for the Reduction of Cycle Time

The goal of any manufacturing firm is to stay competitive in the global market and remain efficient. Cycle time is one of the parameters that manufacturing firms investigate when trying to improve the customer response, efficiency and costs [71]. Therefore, cycle time should be optimised as much as possible [71]. This section looks at some of the methods that are currently used for the reduction of cycle time with the aim to optimise production. These methods are:

- **Lean Manufacturing (LM)** – Lean manufacturing (also referred to as Lean System) can be defined as a technique that consists of tools and practices that aim at continuously eliminating all kinds of waste (non-value-added activities) in the manufacturing process to improve efficiency and the customer responsiveness [61][72]. These tools and practices assist lean manufacturing in reducing the cycle time by reducing the waiting times in the different workstations of the production line [73]. According to Bhamu and Sangwan [74], the lean manufacturing concept was first implemented in the Japanese manufacturing industry, to be specific Toyota [75], when manufacturers realised that it had become costly to invest in rebuilding devasted facilities [74]. The drawback of lean manufacturing systems is more time is spent searching for an accurate solution and as a result latency is very high [76].

- **Heuristics** – Heuristics can be defined as techniques that search for an optimal solution when solving a problem [77]. The use of heuristics to solve real-world problems has increased over the years, as they are also capable of improving on existing optimisation solutions by looking at other possible solutions, while considering the restrictions [78]. One of the advantages of heuristics is that when applied, they provide feedback very quickly and this is very helpful to engineers in the design process, as these results can be used as a benchmark to the initial problem [77]. There are several heuristics that are available and that can be used to reduce the cycle time. Khlil *et al*. [79] used a heuristic named "Greedy" to reduce the cycle time and maximise efficiency in a SALB by reducing the difference between process times of each workstation and the highest process time among all workstations [79]. This proved heuristics to be very fast and effective in obtaining feasible solutions in

SALBP. However, the performance of heuristics does not seem to be satisfying when it comes to large-scale problems such as MALBP, MSP and UALBP [80].

- **Meta-heuristics** – Meta-heuristics can be defined as a class of stochastic algorithms that were developed to be a possible solution to the complex real-world problems (such as MALBP, MSP and UALBP) that heuristics would fail to overcome, as they provide much more improved solutions than heuristics [81]. They do so by using the results of heuristics as a benchmark and then generate a more improved solution in a single run with reasonable computational costs [82]. According to Razali *et al.* [83], the literature reviews that cover Mixed-Model Assembly Lines Balancing Problems find Genetic Algorithm (GA), Particle Swarm Optimisation (PSO), Ant Colony Optimisation (ACO) and the Simulated Annealing (SA) to be the most researched metaheuristic algorithms [83], with GA ranked as the most used in MALBP out of the four algorithms [82], followed by SA, ACO and PSO, in that order [83]. Rabbani *et al.* [84] used metaheuristics in a robotic U-shaped mixed-model assembly line to reduce the cycle time and optimise production [84]. However, none of these studies focused on the reduction of cycle time in multi/mixed-model stochastic straight type assembly line and the inputs are not in real-time in meta-heuristic algorithms.

- **Digital Shadow (DS)** – Industry 4.0 standards in this new digital transformation era have resulted in more challenges in the manufacturing industry [85], one of the challenges being high number of customised customer orders [86]. This has created a need for more complex manufacturing systems that can assist companies in remaining relevant and competitive in the current global market [86]. A Digital Shadow is a virtual data-generating system developed in the on-going digital transformation era to support decision-making in the manufacturing industry for the design and implementation of the complex manufacturing systems [87]. The decision making in DS is near real-time [88]. Digital Shadows have the ability to identify the bottlenecks and monitor, using historical data, the production line, thereby enhancing efficiency and minimising the cycle time [89]. However, Digital Shadows have a one-way data flow, between the physical system and the digital model, which is manual, and the inputs are not in real-time [90].

- **Digital Twins (DT)** – Digitalisation of manufacturing systems has been proven to be one of the ways that can assist manufacturing firms to deal with the increasing number in variety of products and the high customer demand, as it enables transparency throughout the entire production process [91]. Digital Shadows and Digital Twins are the two popular technologies that enable digitalisation in this new digital transformation era [92]. They do so with the help of some the new Industry 4.0 technologies such as Internet of Things (IoT), Big Data, Fifth-generation cellular network (5G), Cyber Physical Systems (CPS), Artificial Intelligence (AI) and Cloud Manufacturing (CM) [93]. However, the Digital Shadow is a by-product of the Digital Twin [94]. The concept of Digital Twin technology has been gaining interest from several manufacturing firms over the past few years, to stay competitive in the global market and above the traditional manufacturing systems [95]. A Digital Twin can be defined as a virtual system that acquires real-time data (enabling real-time interaction) from a real-world system or component and presents it in a digitalised format [96]. The roles of Digital Twins include, but are not limited to, real-time visualisation, analysis of the physical system's performance and optimisation, therefore reducing the maintenance time and the cycle time [92].

2.5.1 Digital Shadow versus Digital Twin

Digital Shadows and Digital Twins are both virtual systems that represent a real-word system and can use the data from the physical system for simulations [97]. However, the data flow and the level of integration is what separates Digital Twins and Digital Shadows [98][99]. In Digital Shadows, the data flow between the virtual system and the physical system is one-way (from the physical system to the virtual system) [100], meaning a change in the state of the physical system will cause a change in the state of the virtual system but not vice versa [101].

It should be noted that the Digital Shadow is not a full representation of the physical system, but it is designed with a specific purpose and can therefore use historical data from the physical system to perform specific tasks [102]. On the other hand, Digital Twins have a bi-directional data flow (between the virtual system and the physical system) [103] and use Digital Shadows as one of the core components that make up a Digital Twin [85].

This is because in Digital Twins there is full integration between the virtual system and the physical system [104]. This is through the help of IoT sensors that are installed on the physical system prior to designing the virtual system (a Digital Shadow), to feed the virtual system with continuous real-time data [105]. A Digital Twin is more than just a simulation model, as Digital Twins can use historical data, depict the present status and predict the future [90].

2.6 Current Use of Digital Twins in Manufacturing

Numerous technology concepts have emerged since the advent of Industry 4.0, one of the technology concepts being the Digital Twin [106]. The interest in the Digital Twin concept has increased throughout the years from different industry sectors with the aim of improving the performance of the physical systems [107]. The concept of a Digital Twin was first proposed by Michael Grieves of the University of Michigan and John Vickers of NASA in 2003 [106], in one of the product life-cycle lectures [108].

A Digital Twin is a virtual system that runs on its own, and with the help of the sensors integrated to the physical system, real-time synchronisation between the physical system and its Digital Twin is enabled [109][110]. Therefore, this makes Digital Twins one of the emerging Industry 4.0 technologies that can support digital transformation and decision making in various fields [111]. The Digital Twin concept originates from the aerospace industry [112]. However, with the value Digital Twins bring, multiple industry sectors such as manufacturing, construction, healthcare and smart farming [113], to name a few, have started utilising Digital Twin technology.

The manufacturing sector is evolving and has therefore been moving towards customised production since the advent of Industry 4.0 [114]. Digital Twins have been proven to be one of the new concepts that has potential to enable efficient smart manufacturing [115]. Digital Twins are often confused to be the same as SCADA (Supervisory Control and Data Acquisition) systems in the manufacturing industry [116]. However, SCADA systems only provide real-time visualisation of the physical system's present status, while DTs can do more than real-time visualisation [116] and one can consider SCADA systems as one of the basic components that make up a DT.

Digital Twins in manufacturing can be used for performing simulations, predictions, real-time controlling in complex working conditions and diagnostics on the physical manufacturing system, other than just visualisation [117]. Feng *et al.* [118] used Digital Twins in the manufacturing sector to create a smart manufacturing environment that is Digital Twin driven for predictive maintenance (with the help of metaheuristics), with the aim to reduce the total maintenance costs and improve decision making [118]. Da Cunha *et al.* [119] looked at the design phase of a Digital Twin and a prototype system of a reconfigurable manufacturing system was developed, to showcase the importance and benefits of DTs during modification of real-world manufacturing systems [119].

2.7 Limitations of Existing Research

As alluded to in the previous sections, this research will specifically focus on the reduction of cycle time in a Mixed-Model Stochastic Straight (MMSS) Assembly Line, which is a system that is designed to adhere the Industry 4.0 requirements, making it a MTO system. As discussed in Section 2.2.2.2, the MMSS assembly lines are for productions where the inputs cannot be predetermined and are hence suitable for MTO systems, as they are stochastic in nature.

There are two groups that MMSS assembly lines can be split into, namely, MMSS type 1 and MMSS type 2. These groups are similar to the SALBP-1 and SALBP-2 types that were discussed in Section 2.3.1, where SALBP-1 is for problems that are concerned with the reduction of number of workstations for a fixed cycle time and SALBP-2 is for problems that are concerned with the reduction of cycle time for a fixed number of workstations.

This research will only be focused on type 2, as the aim is to reduce the cycle time in a MMSS assembly line that has a fixed number of workstations. As seen in the discussion under Section 2.6, at the time of writing this thesis, the amount of research done into the use of Digital Twins in the manufacturing sector was limited and almost no research on the use of Digital Twins in MMSS assembly lines specifically had been done.

Vijayakumar *et al*. [71] studied the reduction of cycle time in manufacturing companies in India using lean manufacturing fused with the Black Widow Based Deep Neural Network (BWDBN) with the objectives to trace and eliminate all kinds of waste in the improved, streamlined process and therefore reducing cycle time [71].

Clarion *et al.* [120] used the simulated annealing metaheuristic in a manufacturing sector to reduce the distance travelled by an automatic guided vehicle (AGV) to transport products in different workstations; this method confirmed that taking into account the shape of the workstation can reduce the distance travelled by the AGV [120].

Aguilar *et al.* [121] used several heuristics and metaheuristics to solve the buffer sizing problem in a parallel assembly line system with multiple workstations and different cycle times, and the results have proven heuristics and metaheuristics to be a better solution for this problem than exact procedures [121].

Lugaresi *et al.* [122] used the Digital Twin architecture in a closed-loop manufacturing system with five workstations and two parallel production lines, with a stochastic processing time for production service control, in order to manage the material flow using simulation-based predictions of the remaining cycle time [122].

The drawback of these studies is that there is very little research on the reduction of cycle time in the manufacturing sector and the techniques that were used to reduce cycle time do not take in real-time data as inputs. Therefore, they are not able to do real-time predictions. Lugaresi *et al.* [122] developed a Digital Twin and were therefore capable of real-time predictions. However, the Digital Twin was not used in a Mixed-Model Stochastic Straight-type (MMSS) assembly line and not for cycle time reduction.

This research aims at optimising and reducing the cycle time in a MMSS assembly line using a data-driven Digital Twin. It is hypothesised that the Digital Twin will reduce the cycle time better than the existing models, as Digital Twins can use real-time data as inputs for future predictions and controlling. Figure 2.6 shows the research localisation of this study.

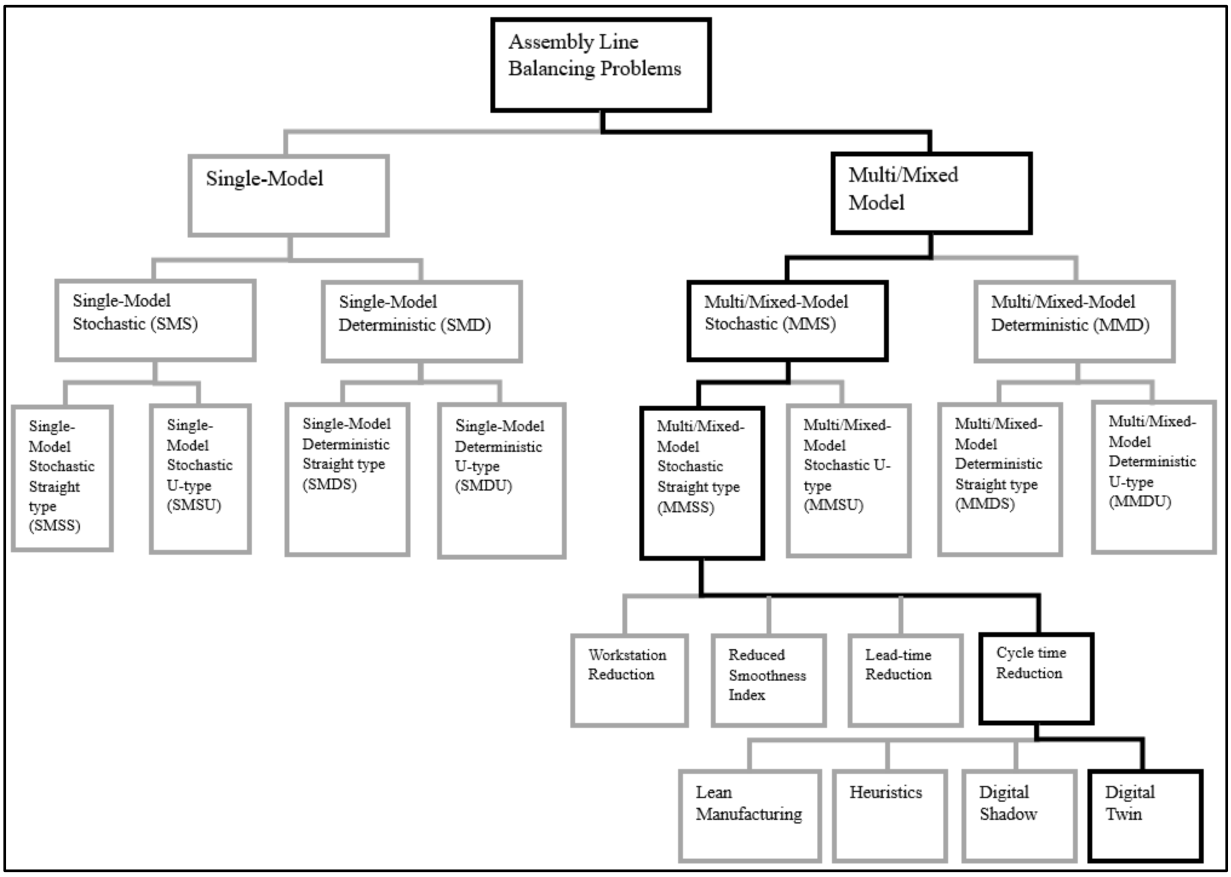

Figure 2.6: Research problem localisation

2.8 Chapter Conclusion

This chapter focused on the different types of assembly lines along with their classification, as part of the literature review. The factors affecting the production time in a manufacturing assembly line, were also addressed in this chapter with cycle time being the main focus. Next, the unique techniques used currently for cycle time reduction were listed and discussed. The chapter was rounded off by looking at the limitations of existing research.

In the next chapter, Chapter 3, the proposed solution of the study as well as the selected case study will be introduced. This chapter will discuss the experimental setup of the study. Next, the different stages of the development of the proposed solution will be detailed.

Chapter 3: Methodology

3.1 Introduction

The aim of the study is to develop a data-driven Digital Twin for a mixed-model stochastic system to monitor the process flow in real-time in order to reduce cycle time and enhance production efficiency. This chapter discusses the research methodology that was undertaken to address the challenges mentioned in the limitations of existing research, in Section 2.7.

In this chapter, the design and development of the two virtual models of the water bottling plant will be discussed. These models will be designed using the *MATLAB* and *SIMULINK* platforms. The first model is a Digital Shadow, and the second model will be the Digital Twin. The Digital Twin will be fed with continuous real-time data through a cloud server and the results of the Digital Twin will be compared with that of the Digital Shadow in the results section, to showcase the impact real-time inputs have on cycle time reduction.

A real-world system is needed when developing a Digital Twin and, in this case, a smart water bottling plant at the Central University of Technology in the Free State (Bloemfontein campus) was selected as this is where the study was conducted. As discussed in Section 1.3.2, the research methodology will be implemented in these three stages:

- *Step 1* – The design and development of a Digital Shadow.
- *Step 2* – Integration of sensors to the physical system. Providing the real-time data as inputs to the Digital Shadow. Therefore, converting the Digital Shadow into a Digital Twin.
- *Step 3* – Analysing and comparing the cycle times calculated by the Digital Shadow and Digital Twin, to showcase the impact of real-time data.

The next section details the consideration of the plant and why it was selected for this study.

3.2 The Water Bottling Plant – A Case Study

As alluded to in Section 3.1, a real-world system is needed for developing a Digital Shadow and its Digital Twin. It is for this reason that a water bottling plant was selected as the case study for this study. The water bottling plant was based on a business plan that was developed and implemented at the Central University of Technology (CUT) [123].

This water bottling plant is made up of two parallel production lines which can be configured either as parallel, straight line or in a U-shape. However, for this study only one of the two production lines was used and in a straight-line layout, as shown in Figure 3.1. Therefore, the water bottling plant was considered for this study, as the assembly line layout of the water bottling plant was configured in a straight-line layout and was designed to fulfil the demand of product variety in the current global market. Thereby, this made the plant a Mixed-Model Stochastic Straight (MMSS) type assembly line.

Figure 3.1: Water Bottling Plant assembly line layout

This water bottling plant is made up of three Smart Manufacturing Units (SMUs), for filling, capping and packaging, as shown in Figure 3.2. However, this study will only focus on SMU 1 and 2, since the aim is to reduce cycle time and cycle time is considered as the time it takes to convert raw materials into a complete product. Therefore, SMU-3 will be omitted from this study.

The plant is designed to produce two variants of water bottles, namely, 330ml and 500ml bottles. These SMUs are connected end-to-end in a straight-line layout, where each SMU is driven by the Siemens S7-1200 Programmable Logic Controller (PLC). Table 3.1 details the function and execution of each SMU.

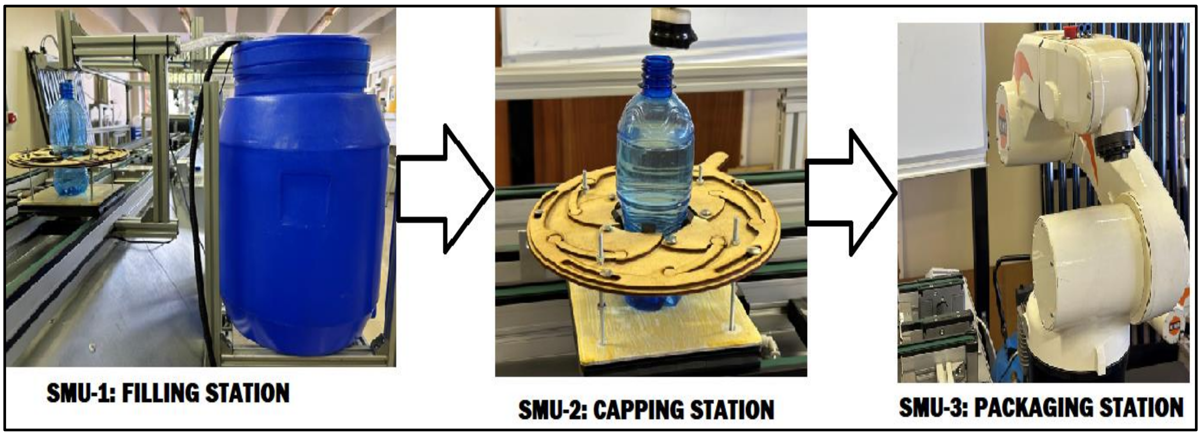

Figure 3.2: Smart Manufacturing Units

Table 3.1: SMU function and execution

SMU	**Function**	**Execution**
SMU-1	Filling	S7-1200 PLC
SMU-2	Capping	FESTO Gripper
SMU-3	Packaging	KUKA Robot

3.3 The Experimental Setup

This section details the experimental setup that was undertaken in achieving the hypothesis of this study mentioned in Section 1.3.1. The Digital Shadow and Digital Twin models that are designed for the Mixed-Model Stochastic System in this study, were tested using the same set of customer orders as inputs and the results of the models compared thereafter. This was done to showcase the impact the Digital Twin has in the reduction of cycle time and ensuring an efficient production line.

Even though the Digital Shadow and Digital Twin are designed for the same system, the programming behind the Digital Shadow and the Digital Twin is different, and therefore do not operate the same. The water level is 100% at the beginning of every customer set for both the Digital Shadow and the Digital Twin. The programming behind the Digital Shadow and Digital Twin models is detailed in Table 3.2.

The Digital Shadow uses the formula in equation 1 to monitor the water level in the tank. This is done by calculating the amount of water required to complete a single order and comparing it to the remaining water in the tank. The operator decides as to when to do a refilling based on these calculations. The Digital Shadow is programmed to have some pauses during production, and the duration of these pauses is determined by the water level, to allow refilling, as shown in Figure 3.3.

$$Number\ of\ Bottles = \frac{Water\ Required\ (L)}{Bottle\ Size\ (mL)} \qquad (1)$$

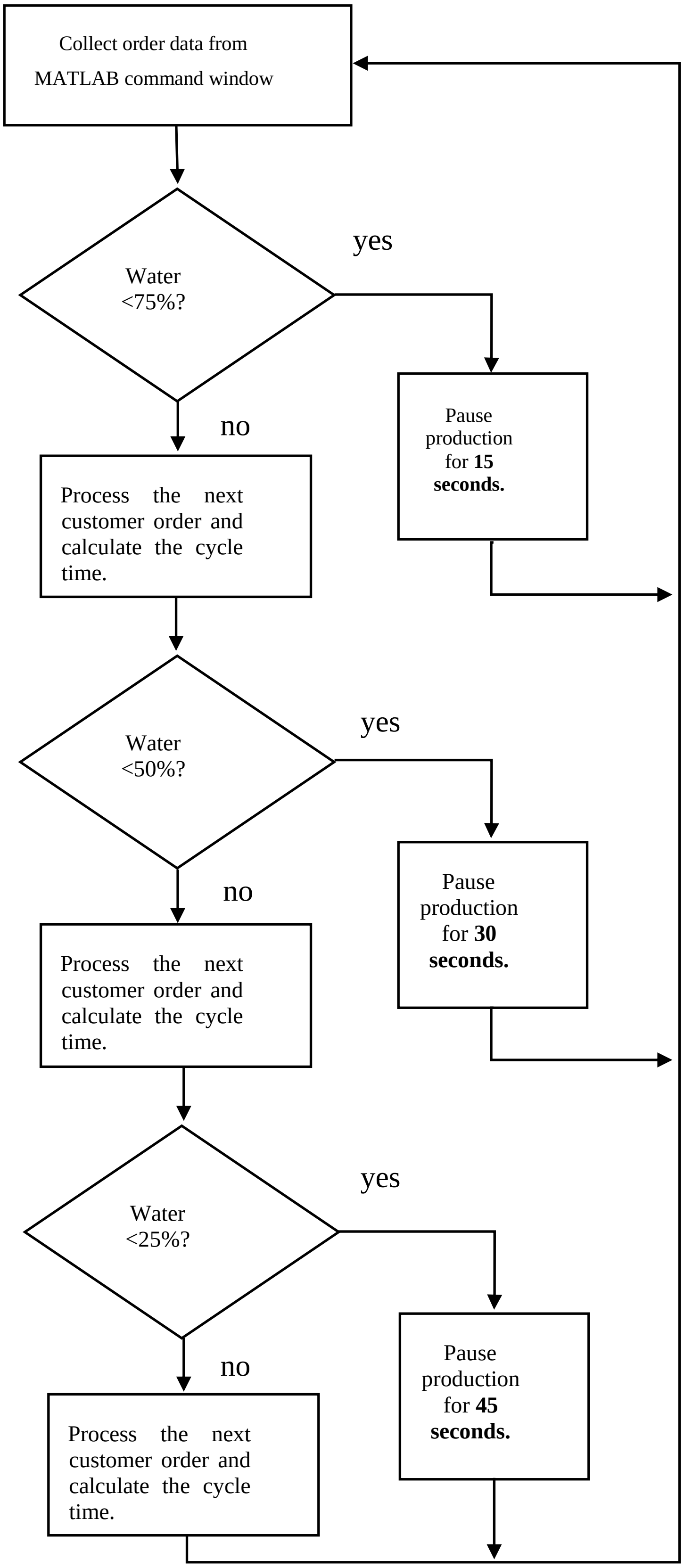

Figure 3.3: Digital Shadow flowchart

Unlike the Digital Shadow, the Digital Twin model uses the real-time data provided by the IoT sensors, which are installed and integrated to the mixed-model stochastic system. Therefore, making a Digital Twin more than just a simulation model, as the real-time data enables the Digital Twin to visualise and monitor the water level, the flowrate and the number of complete orders, in real-time. Therefore, no pauses to the production process are required in the Digital Twin, as the refilling of the tank and the processing of orders can happen concurrently without affecting the efficiency of the system. The programming of the Digital Twin is as shown in Figure 3.4.

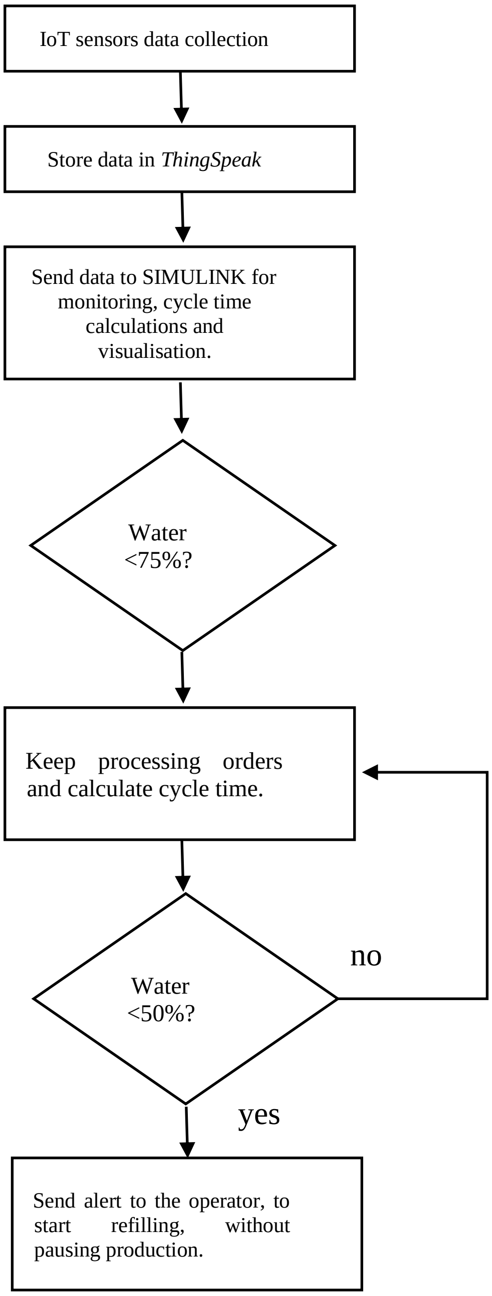

Figure 3.4: Digital Twin flowchart

Table 3.2: Operation of the Digital Shadow and Digital Twin

Water Level	**Digital Shadow**	**Digital Twin**
100%	Process the next order.	Process the next order.
< 75% but > 50%	Pause production for 15 seconds before processing the next order.	Process the next order.
< 50% but > 25%	Pause production for 30 seconds before processing the next order.	Alerts the operator, to refill the tank. NB: No pauses to the production.
< 25% but > 0%	Pause production for 45 seconds before processing the next order.	Alerts the operator, to refill the tank. NB: No pauses to the production.

Table 3.2 shows that the Digital Shadow is programmed to pause production for 15 seconds before processing the next order, and if there is no refill to the tank and the water level goes below 50%, the pausing time of production is doubled, resulting in the pausing time now being 30 seconds. If the tank is still not refilled and the water level drops below 25%, another 15 seconds is added, resulting in a pausing time of 45 seconds. On the other hand, the Digital Twin uses IoT sensors to monitor the water level and alerts are sent to the operator continuously as soon as the water level drops below 50% and there are no stops to the production.

3.4 The Development of a Digital Shadow

The development of a Digital Shadow is one of the first and most important stages when designing a Digital Twin. Therefore, a Digital Shadow that uses dummy data to calculate the cycle time was developed in this section. Digital Shadows are similar to the heuristics, metaheuristics and lean manufacturing techniques discussed in Section 2.6, in that the inputs are not in real-time.

The final Digital Shadow model created on *SIMULINK* is shown in Figure 3.5. Two "From Workspace" blocks are used to collect data from the *MATLAB* "Workspace" and use it as inputs to the model. This will be done using the two variables named X and Y. The variables must be declared according to the customer orders, as X is the number of 500ml bottles and Y is the number of 330ml bottles.

The two "multiply" blocks represent the time a 500ml bottle takes to complete the tasks in SMU-1 and SMU-2 each, similarly with the 330ml bottle. The two 500ml bottle "multiply" blocks are added together using the "adder" block, similarly with the 330ml. The outputs of these 330ml and 500ml bottles' "adder" blocks are added to another "adder" block of which the output is the net production time. Net production time is calculated as the time it takes for a bottle or bottles to complete the tasks in SMU-1 and SMU-2. The net production time divided by the total number of products produced results in the production cycle time, as shown in equation 2.

$$Cycle\ Time\ (CT) = \frac{Net\ Production\ Time}{Number\ of\ Units\ Produced} \tag{2}$$

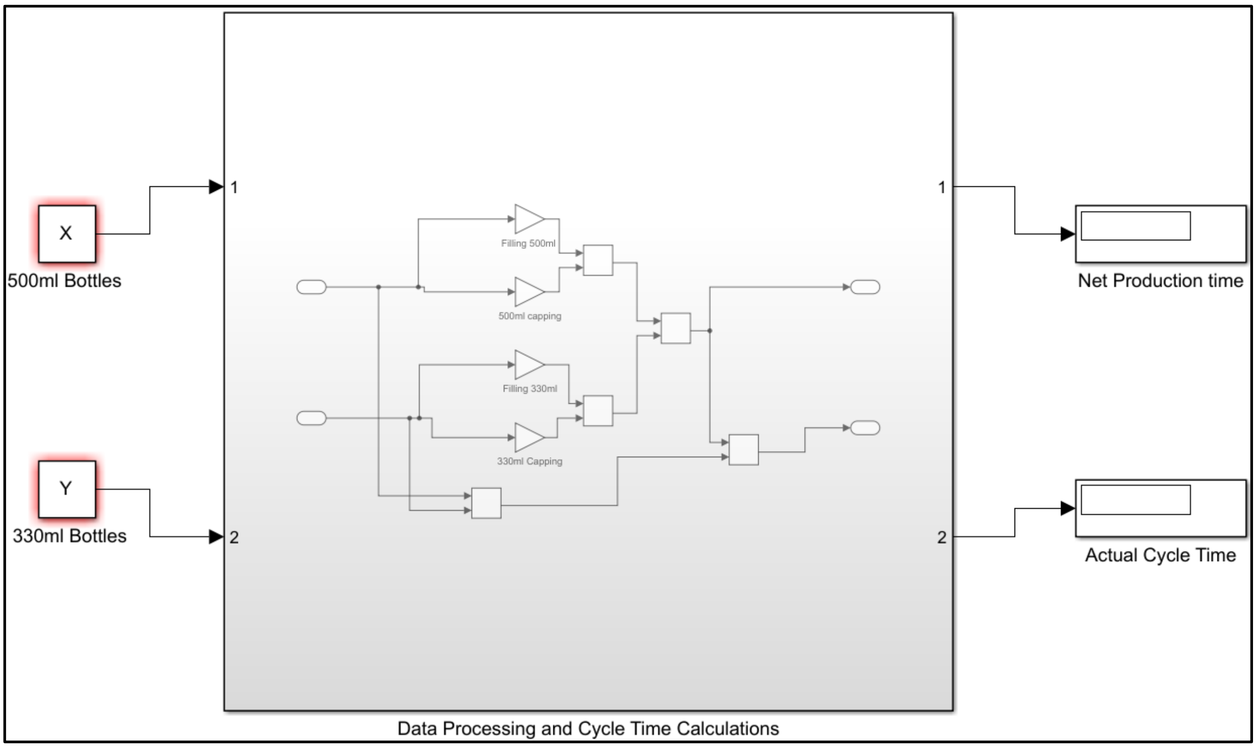

Figure 3.5: Digital Shadow model on SIMULINK

3.5 The Development of a Digital Twin

This section details how the research methodology of developing the data-driven Digital Twin was conducted, from the selection and integration of IoT sensors along with the cloud platform that is compatible with the selected IoT sensors for data logging, to converting the Digital Shadow model into a Digital Twin model by using real-time data as inputs. The design and development of the data-driven Digital Twin is split into three stages, as shown in Figure 3.6.

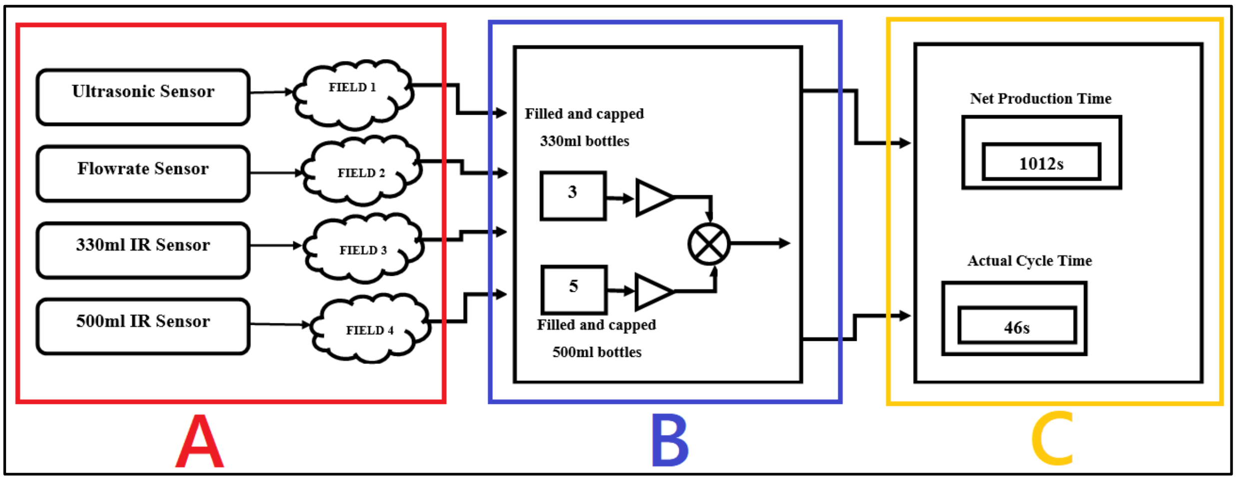

Figure 3.6: Three stages of the development of a Digital Twin

The three stages of the development of a Digital Twin with their specific tasks are as follows:

- STAGE A – Data collection
- STAGE B – Data processing and cycle time calculations
- STAGE C – Cycle time monitoring

A *SIMULINK* model with three different subsystems is shown in Figure 3.7. The three stages of the development of a Digital Twin described in Figure 3.6 are shown in the *SIMULINK* model.

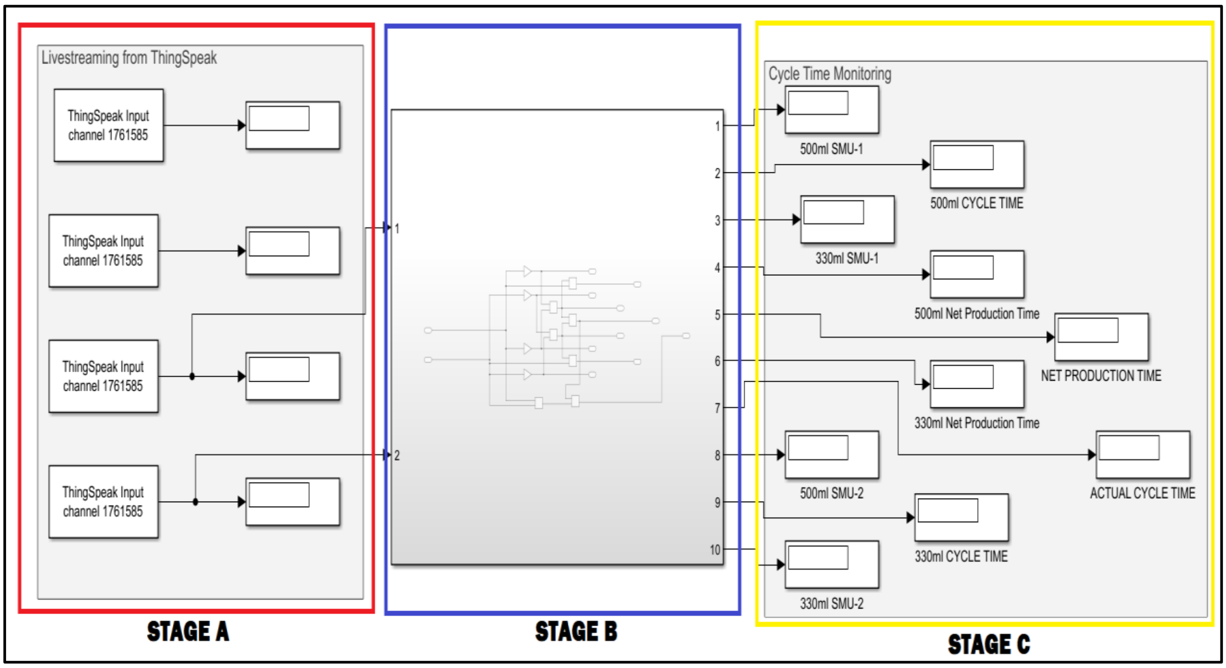

Figure 3.7: SIMULINK model that depicts the three stages of a Digital Twin

Each of these subsystems are well detailed in the next sections, from stage A, stage B and then stage C.

3.5.1 STAGE A – Data collection

To collect data, a data collection system must be set up. Literature has shown that there are multiple technologies available that can be used to form a data collection system [124]. However, the method used in the data collection system in this study is the Internet of Things (IoT). IoT is one of the technologies in the ongoing Industry 4.0 which enable real-time integration and synchronisation between the digital and the physical system [124]. Therefore, the selection of IoT sensors is one of the first and most significant stages when setting up a Digital Twin model. The selection of IoT sensors relies on the aspects that the virtual model wishes to monitor and control. Therefore, wrong selection of IoT sensors may result in the designed virtual model not functioning as expected.

The aspects that needed to be monitored by the Digital Twin for the manufacturing system in this study are: the water level in the filling tank, the flowrate, and the number of filled and capped 330ml and 500ml water bottles. As a result, the following IoT sensors were identified and selected for the Digital Twin model constructed in this study:

- Weather-proof Ultrasonic sensor – To monitor the water level in the filling tank in SMU-1.
- Flowrate sensor – To monitor the water flowrate in SMU-1.
- Adjustable infrared (IR) Proximity sensor – To monitor the number of filled and capped 330ml and 500ml water bottles in SMU-2.

This data collection system uses the ESP32 microcontroller as the processing unit of the system, as all the selected IoT sensors are connected to ESP32 microcontroller. The microcontroller has a built-in Wi-Fi module which enables wireless connectivity between the microcontroller and the Wi-Fi network. The setup of this data collection system is shown in Figure 3.8.

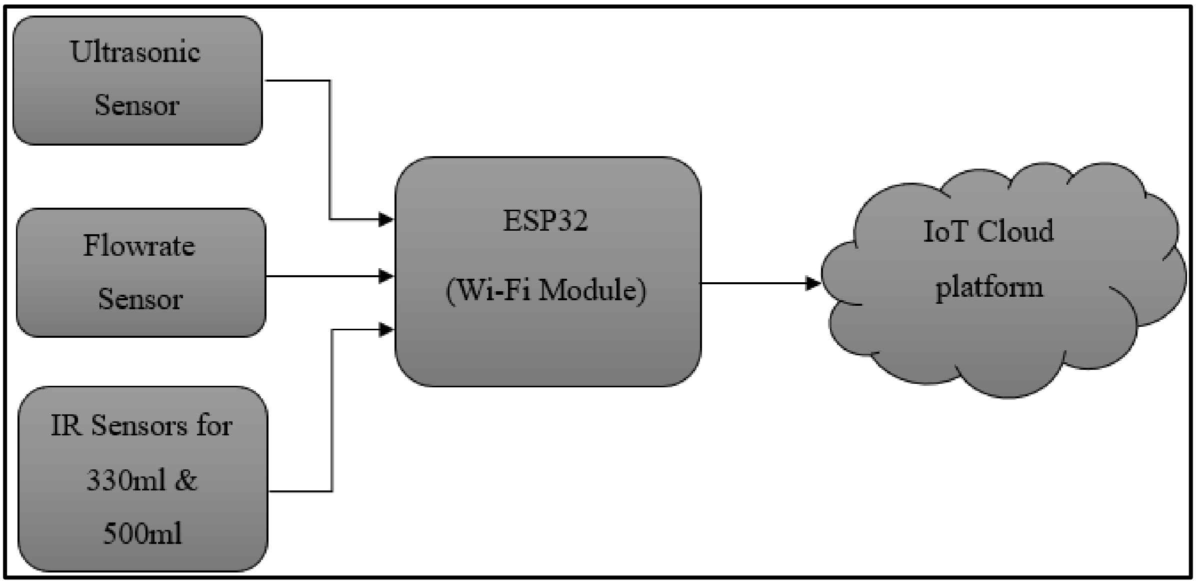

Figure 3.8: Data collection system setup

The microcontroller collects and processes the data from the IoT sensors and send the data to the cloud for storage. There have been hundreds of cloud platforms released since the advent of IoT [125]. However, the cloud platform used in this study is *ThingSpeak*, as it has built-in libraries that support IoT devices and allow data collection, data visualisation and data analysis of real-time data [125]. Another reason for the selection of the *ThingSpeak* platform is the easy interface and data processing of the platform, and the support for *MATLAB* language and *MATLAB* toolboxes [125].

3.5.1.1 Integration of Internet of Things sensors

The IoT sensors were installed and integrated into the water bottling plant after the data collection system had been set up, see Figure 3.9. As mentioned in Section 3.2, packaging (SMU-3) is not aligned with the objectives of this study. Therefore, SMU-2 is considered the last workstation in the production. A weather-proof ultrasonic sensor and the flowrate sensor were installed in SMU-1 and the two IR sensors (for 330ml and 500ml bottles) were installed at the end of SMU-2, as shown in Figure 3.9.

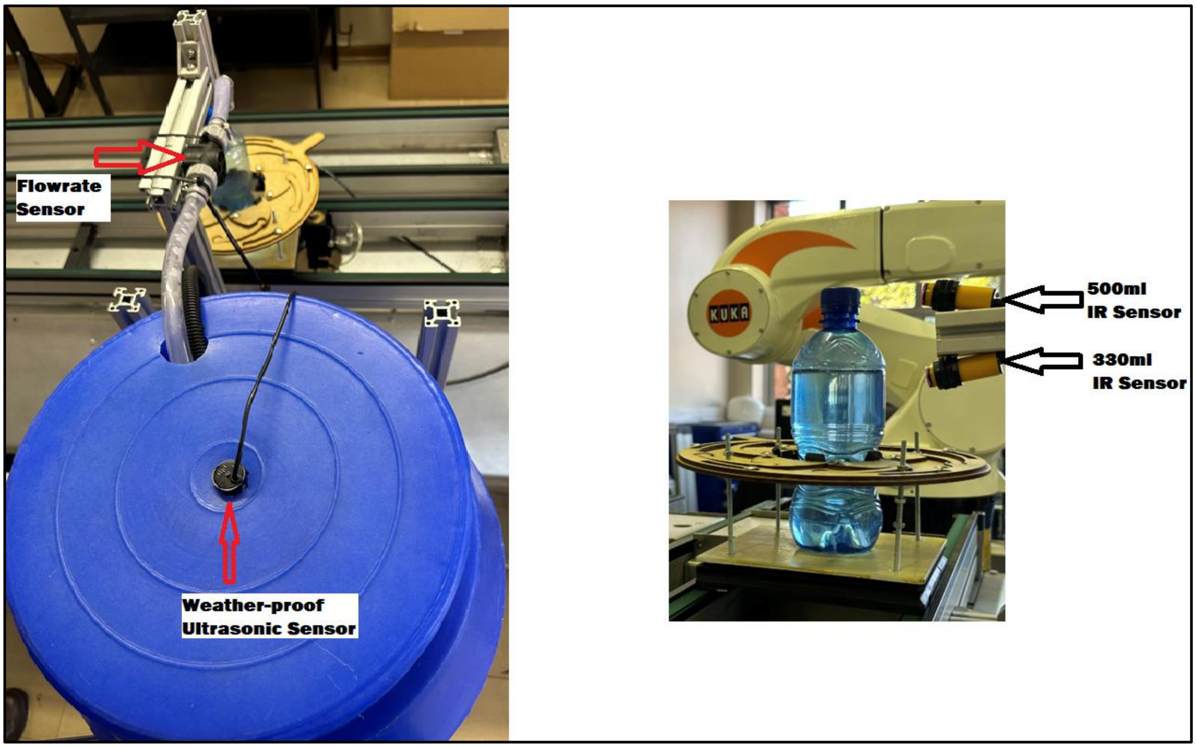

Figure 3.9: Installing IoT sensors to the plant

3.5.1.2 Sensor calibration

The filling tank capacity is 50 litres and the distance from where the ultrasonic sensor (on the lead) is installed to the base of the tank is 50 centimetres (cm). However, the ultrasonic sensor is calibrated to start measuring from outside the radius of 20cm. Therefore, the tank will not be filled to the maximum capacity; this means the 20cm will be subtracted from the 50cm to accommodate the sensor specifications. This means the tank's maximum capacity will now be 30 litres and the sensor will detect 20cm when the tank is filled to the maximum capacity and the distance will start increasing as the water is utilised.

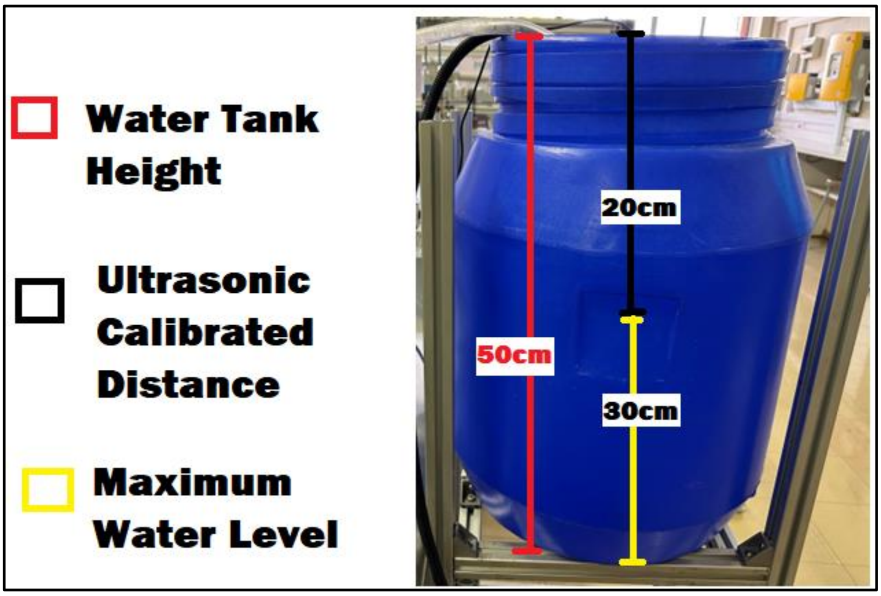

Figure 3.10: Water tank

The two infrared sensors were installed at the end of the production line, as shown in Figure 3.9. The infrared sensors function as counters, one for filled and capped 330ml bottles, and one for filled and capped 500ml bottles. These sensors function as the AND logic gate, when both sensors detect a bottle, a 500ml bottle is counted, when only the below sensor detects a bottle, a 330ml bottle is counted.

3.5.1.3 Creation of a channel for data storage on *ThingSpeak*

A channel with the name "WATER BOTTLING PLANT" was created on *ThingSpeak*. This channel stores data collected from the four IoT sensors and is split into four different fields, as shown in Figure 3.11.

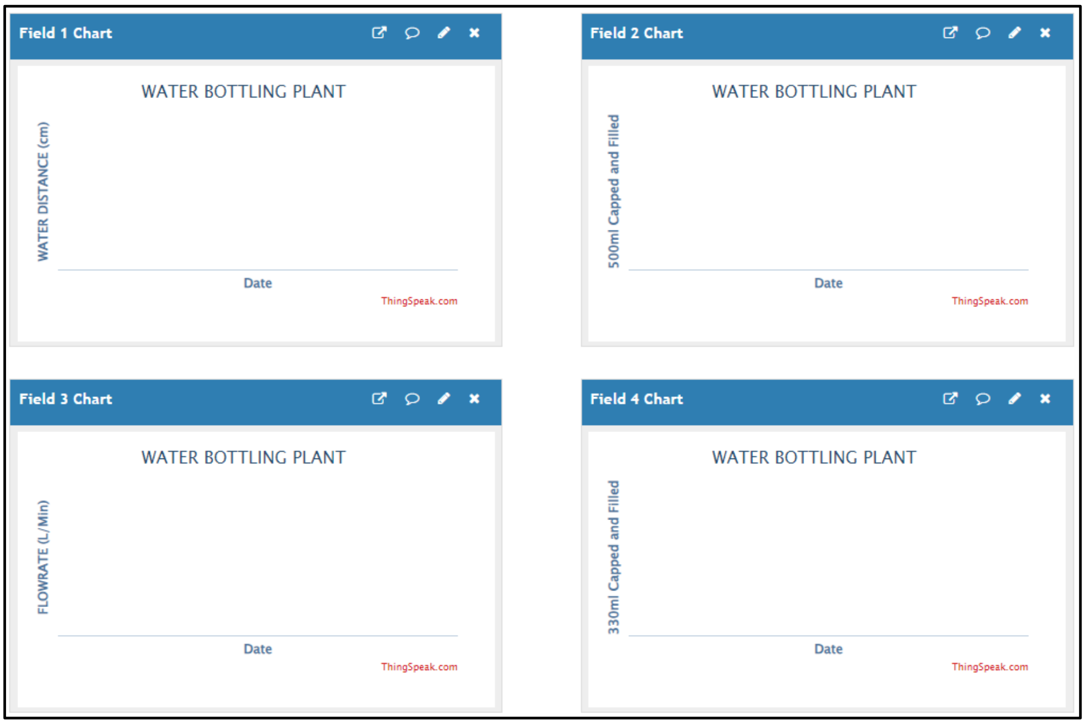

Figure 3.11: "Water Bottling Plant" channel on ThingSpeak

The stage A subsystem consists of two main blocks, which are the *ThingSpeak* input block and the Display block, as shown in Figure 3.12. The *ThingSpeak* input block enables real-time synchronisation between the *ThingSpeak* channel, and the *SIMULINK* model and the Display block displays the last value that was sent to the field.

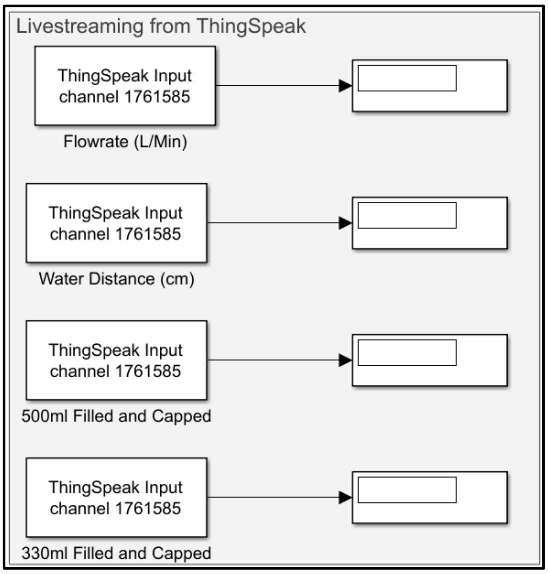

Figure 3.12: ThingSpeak input block setup

Figure 3.13 shows how to configure the *ThingSpeak* input block parameters. The channel ID and the API read key of the "Water Bottling Plant" channel are needed to link the *SIMULINK* model to the channel, also the field which the *ThingSpeak* input block must livestream from needs to be specified.

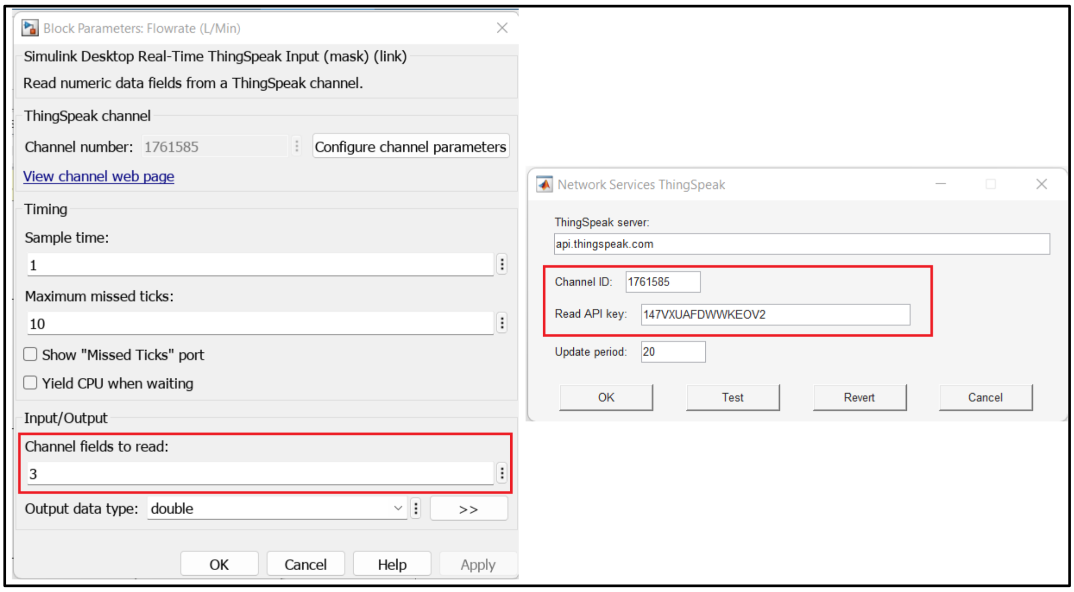

Figure 3.13: Configuring the ThingSpeak block parameters

3.5.2 STAGE B – Data processing and cycle time calculations

This section discusses the development of the Digital Twin model. The data from the IoT sensors in Section 3.4.1 is processed in this section and the calculations of cycle time are made. The Digital Shadow and the Digital Twin developed in this study will be given the same set of inputs to calculate cycle time. The cycle times of these two models will be compared in the Results section, to showcase which one is more efficient.

The live data from the IoT sensors discussed in Section 3.4.1 is used as inputs to the Digital Shadow that was created in Section 3.3. Therefore, converting the Digital Shadow into a Digital Twin, as one of the elements that separate the Digital Twins from the Digital Shadows is real-time inputs. A few changes were made to the Digital Twin, which will be detailed in the Results section.

Shown in Figure 3.14 is the conversion of the Digital Shadow model (depicted in Figure 3.5), on *SIMULINK*, to a Digital Twin by providing the real-time data from the IoT sensors to the model as inputs. The Digital Twin model uses the real-time data from the two infrared sensors to calculate the cycle time as the plant is stochastic and, through the real-time data from the infrared sensors, the model can also be stochastic when processing and calculating the cycle time. However, it should be noted that this model is not only limited to stochastic systems.

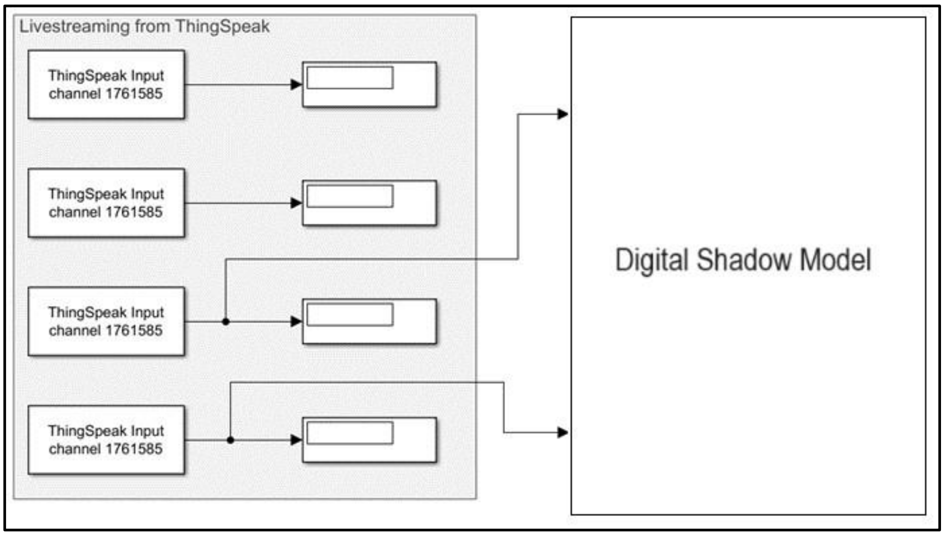

Figure 3.14: Digital Shadow conversion

A dashboard for the Digital Twin model was also developed on *SIMULINK*. This dashboard functions as a SCADA (Supervisory Control and Data Acquisition) system, as the water level, flowrate and the number of filled and capped bottles can be monitored through the dashboard. The operator can keep track of the raw materials through the simplified visualisation provided by the dashboard, as shown in Figure 3.15.

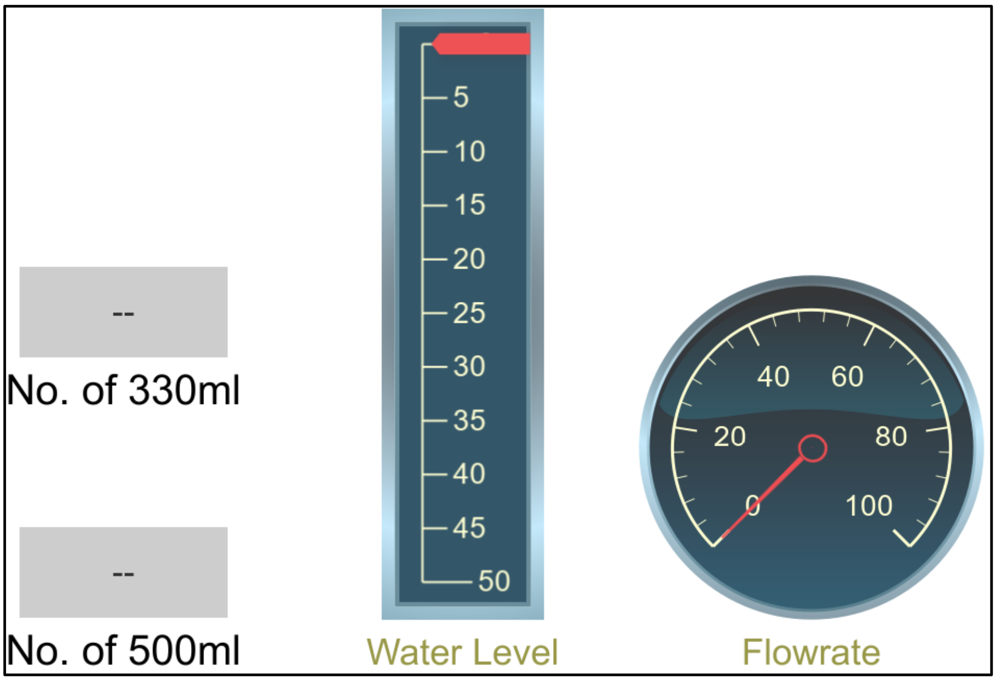

Figure 3.15: Digital Twin dashboard

Figure 3.16 provides a detailed overview of what makes a Digital Twin, as it is common to confuse Digital Shadows and SCADA systems for Digital Twins. However, Digital Twins are more than just simulation and visualisation models; in fact, Digital Twins use Digital Shadows and SCADA systems as some of the basic tools that makes up a Digital Twin.

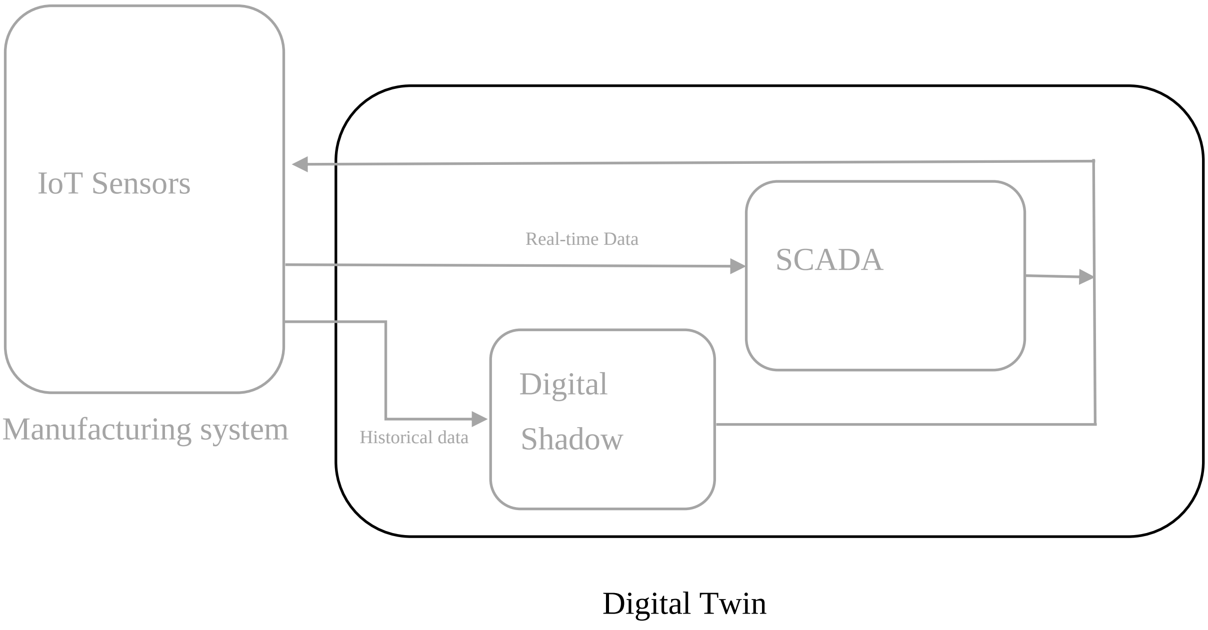

Figure 3.16: Digital Twin overview

3.5.3 STAGE C – Cycle time monitoring

After the data collection by IoT sensors, the data processing, and cycle time calculations discussed in the previous sections, the calculated cycle time values must be displayed. Therefore, this section is responsible for displaying and monitoring the cycle time.

The *SIMULINK* “display” blocks are used to display the cycle times calculated, as shown in Figure 3.17. The net production time and cycle time of the two types of bottles produced by the plant will be displayed individually. Also, the actual net production time and cycle time will be displayed, proving that the Digital Twin model is more suitable for a mixed-model stochastic assembly line.

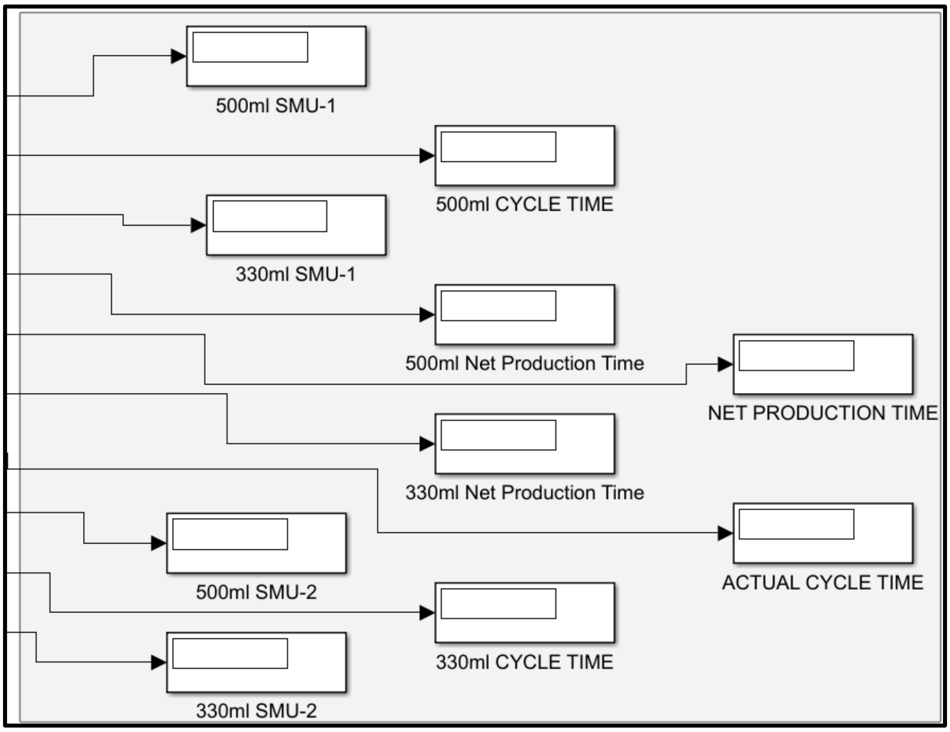

Figure 3.17: Digital Twin cycle time display blocks

The Digital Shadow created in Section 3.3 will also display the calculated net production time and cycle time, as shown in Figure 3.18. This cycle time value will be compared to the cycle time of a Digital Twin to showcase which model will keep the production efficient.

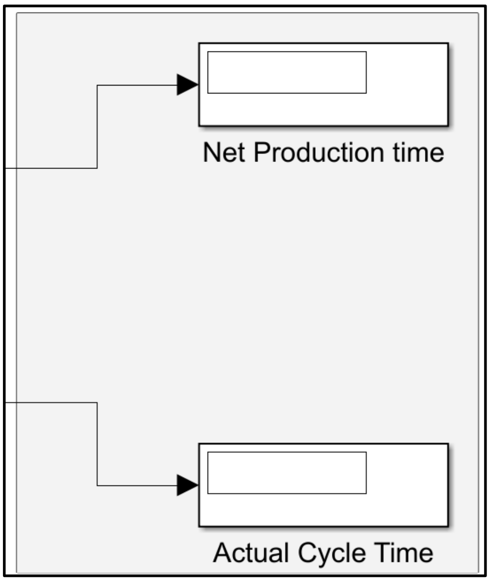

Figure 3.18: Digital Shadow cycle time display blocks

3.6 Chapter Conclusion

The focus in Chapter 3 was on the research design and methodology used in the study and all the procedures that were followed. The chapter introduced the Water Bottling Plant case study and highlighted the reasons it was selected for this study. The experimental setup and the development of the primary model (Digital Shadow) was discussed. The different stages of developing the data-driven Digital Twin model were also highlighted and discussed.

In the next chapter, Chapter 4, the analysis of the output data obtained from the experiments will be discussed and presented as results. Customer orders in different scenarios will be introduced and the results for each scenario will be shown. The aim is to show the impact that real-time inputs have on the production efficiency.

Chapter 4: Results

4.1 Introduction

This chapter aims to showcase the results of the tests and experiments that were done in the process of developing the data-driven Digital Twin model. The sequence of developing a Digital Twin was discussed in Chapter 3 and the same sequence will be used to discuss and analyse the results in this chapter. Therefore, the first tests are done on the Digital Shadow model and the results are discussed thereafter. Next, the tests and results of the Digital Twin model using real-time inputs will be laid out. Finally, a comparison between the tests and results of a Digital Shadow and the Digital Twin will be presented.

4.2 Results of the Digital Shadow Design

Prior to the development of the Digital Shadow model in Figure 4.1, a test experiment was conducted manually to determine the time each bottle takes on SMU-1 and SMU-2. The results are as shown in Table 4.1. The average time it takes for a single 500ml water bottle to complete all the tasks in SMU-1 is 25 seconds and the average time it takes in SMU-2 is 23 seconds. The 330ml water bottle takes 21 seconds in SMU-1 and 23 seconds in SMU-2. The time a 330ml bottle and a 500ml takes in SMU-1 differs, due to the difference in the size of the bottles, which then affects the filling time. However, the time the bottles take on SMU-2 is equal, see Table 4.1.

Table 4.1: Test experiments

Number of Samples	Time taken by 500ml bottle in SMU-1	Time taken by 500ml bottle in SMU-2	Time taken by 330ml bottle in SMU-1	Time taken by 330ml bottle in SMU-2
1	25s	22s	20.89s	22s
2	24.64s	22.90s	21s	22.90s
3	25.04s	22.13s	20.96s	22.13s
4	25.04s	21.74s	21.02s	21.74s
5	24.89	21.97s	21.01s	21.97s
Average	25.722	22.148	20.97	22.148

Figure 4.1 demonstrates how the Digital Shadow model calculates cycle time. The values from the experiment detailed in Table 4.1 are used as gain on each multiplier block, for 330ml and 500ml bottles, respectively. Combining the time taken by each bottle in both SMU-1 and SMU-2 amounts to 48s for the 500ml bottle and 44s for the 330ml bottle. The inputs (X and Y) of this model are declared on *MATLAB* “command window” and stored in “Workspace” as arrays.

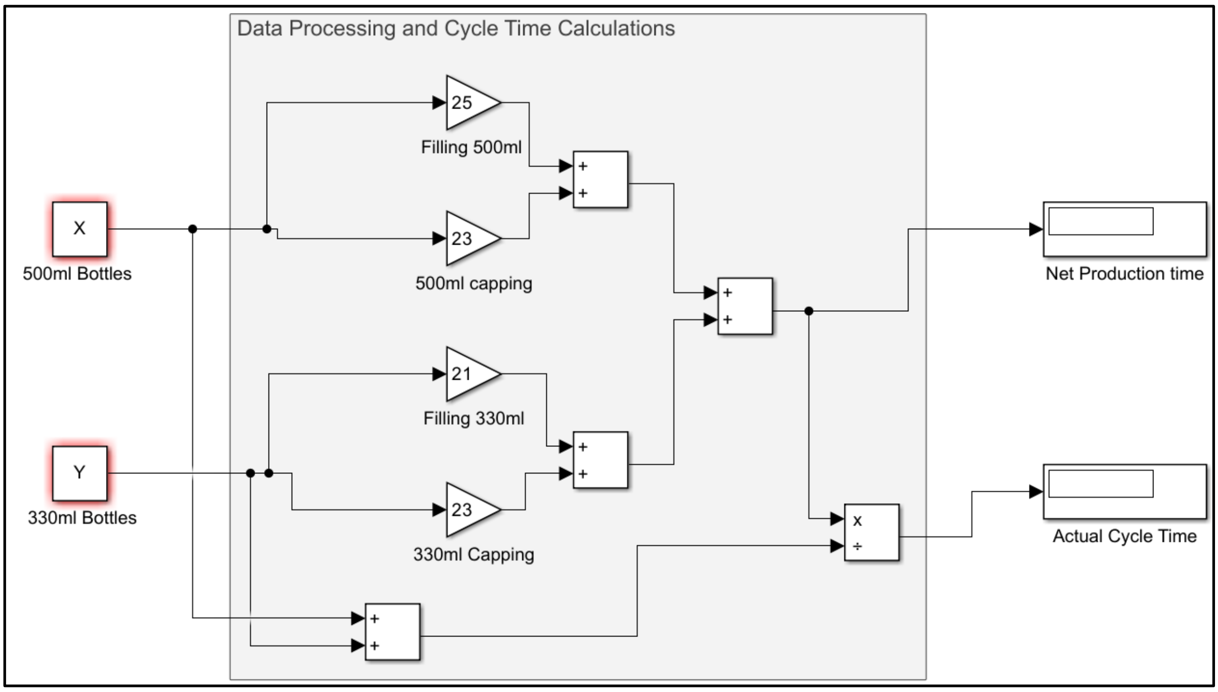

Figure 4.1: Development of a Digital Shadow model for cycle time calculations

4.3 Data Collection Results

A data collection system which consists of four IoT sensors was developed and integrated into the water bottling plant, as discussed in Section 3.5. Figure 4.2 shows the data from the IoT sensors during the actual operation of the plant. All four *ThingSpeak* fields are populated with the live data from the four IoT sensors. As discussed in Section 3.5, the ultrasonic sensor starts measuring from 20cm. During the initial stages of production, the water level is at full capacity, as the ultrasonic sensor measures 20cm. However, as the number of filled and capped 500ml and 330ml bottles increases, the distance between the ultrasonic sensor and the water increases.

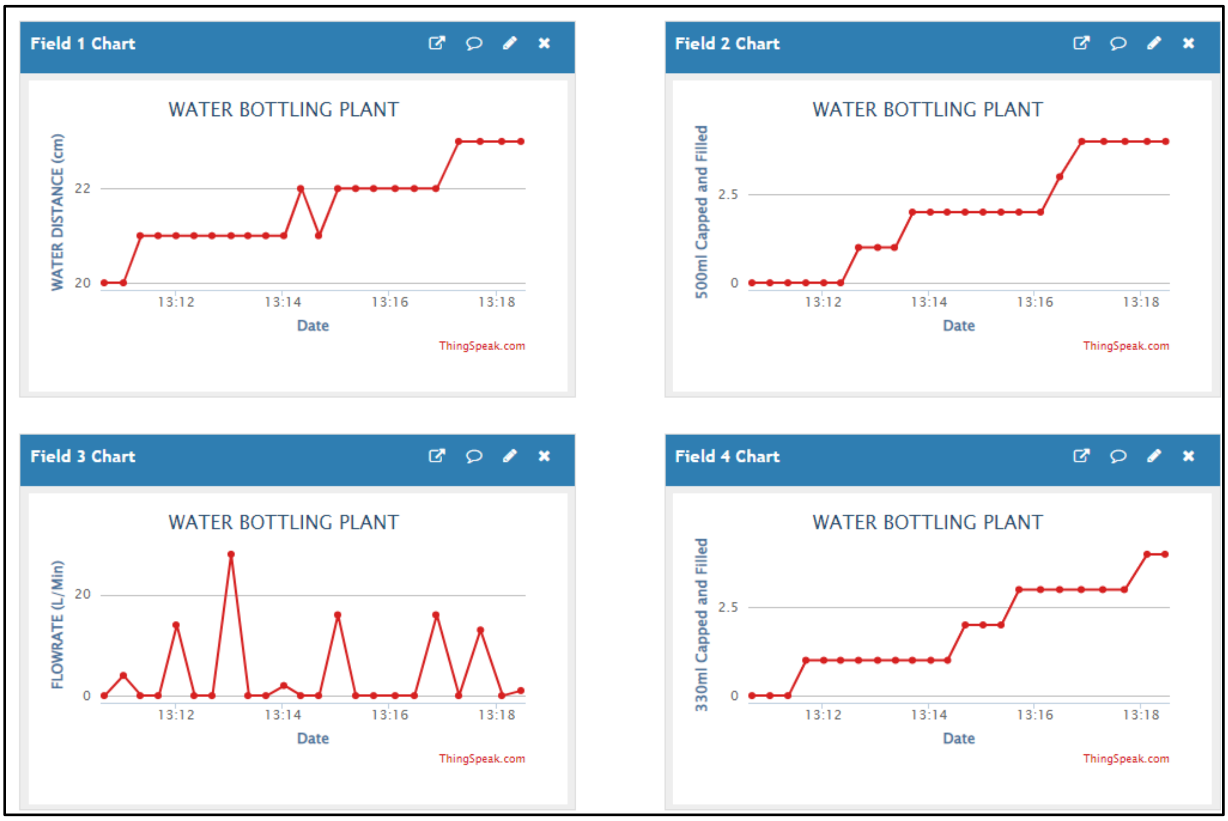

Figure 4.2: ThingSpeak populated with live data

Figure 4.3 shows the live data from *ThingSpeak* being livestreamed and fed as inputs to the Digital Twin model. As shown in the image, the model uses the last updated value on the *ThingSpeak* field. The number of filled and capped 500ml bottles is 4, the number of filled and capped 330ml bottles is 4, the distance between the ultrasonic sensor and the water is 23cm, and the flowrate is 18L/min.

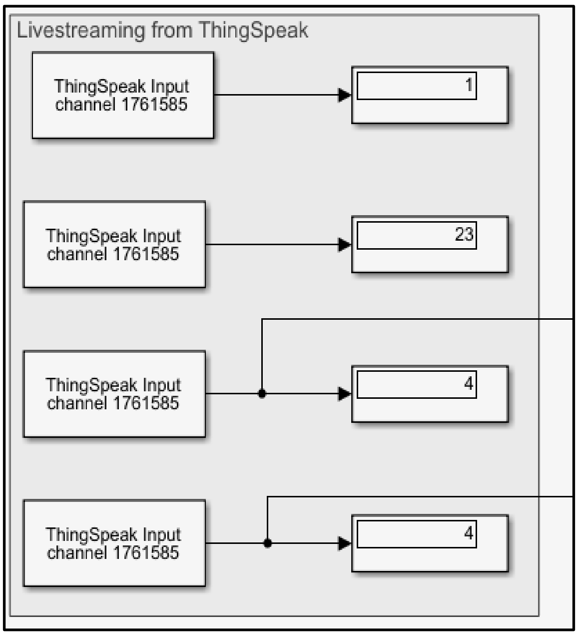

Figure 4.3: Livestreaming from ThingSpeak

4.4 Data Processing and Cycle Time Calculations Results

In order to convert a Digital Shadow into a Digital Twin, “adder” blocks are added to the Digital Shadow. One noticeable change is the inputs, as Digital Twins work with real-time inputs. This will facilitate the integration of real-time inputs and thereby enable the calculation of the cycle time and the net production time of each type of bottle. This is depicted in Figure 4.4.

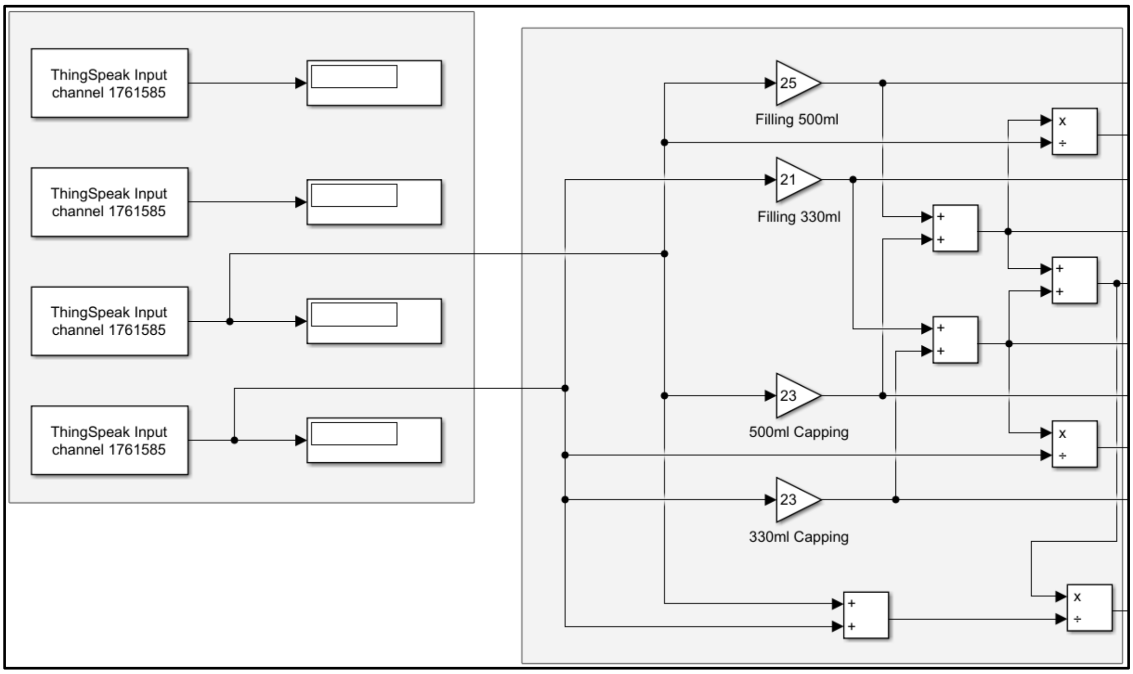

Figure 4.4: Converting a Digital Shadow to a Digital Twin

Figure 4.5 shows the real-time data livestreamed from *ThingSpeak* being utilised as the new inputs in the Digital Twin model. The model uses the last value updated in the channel fields; the values are the same as in Figure 4.2 under Section 4.3.

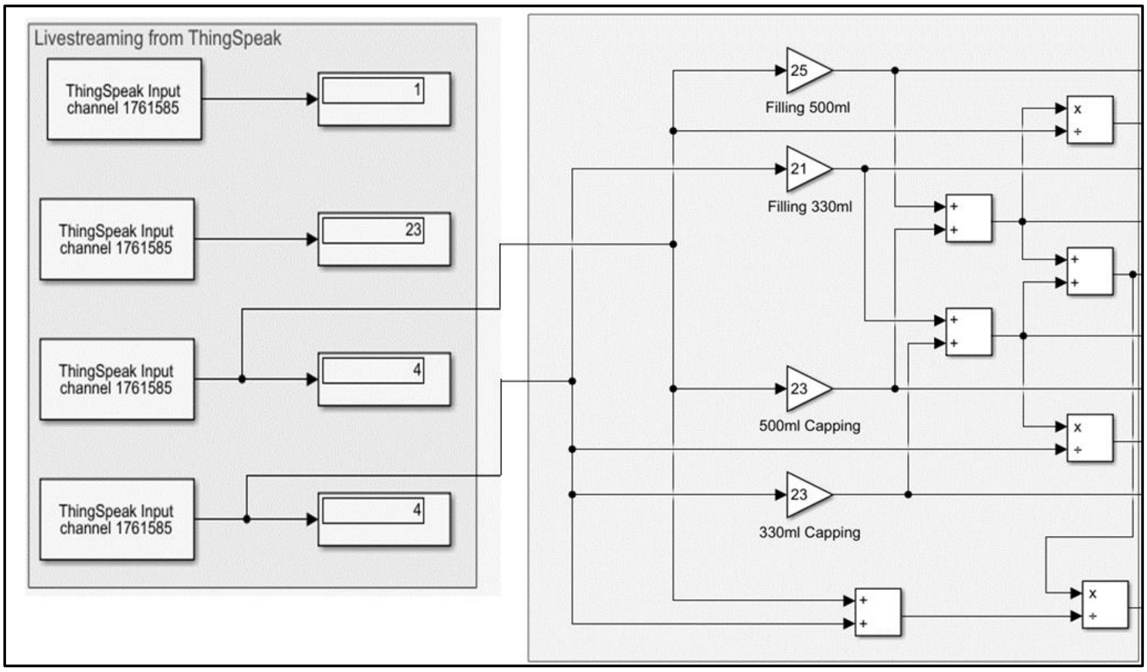

Figure 4.5: Digital Twin using real-time data as inputs

The dashboard that is connected to the Digital Twin model on *SIMULINK* is shown in Figure 4.6. The dashboard provides a more detailed and simplified visualisation of the live data from the *ThingSpeak* fields. It shows the exact number of bottles that have been filled and capped, how much water is left in the filling tank, as well as the water flowrate. The delay in updating data by *ThingSpeak* affects the capturing of the flowrate.

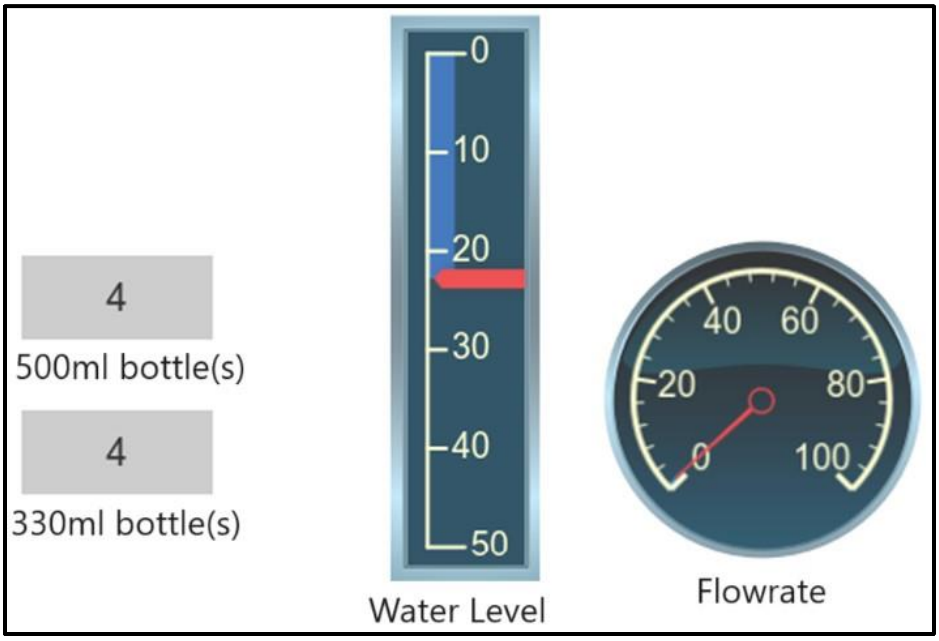

Figure 4.6: Real-time data on the dashboard

4.5 Cycle Time Monitoring

The Digital Shadow model created in this study uses the data from *MATLAB* “workspace” as inputs to calculate the value of cycle time. After data processing and cycle time calculations, the calculated value must be displayed. Figure 4.7 shows the net production time and cycle time value calculated by the Digital Shadow model with the four 500ml bottles and four 330ml bottles customer order.

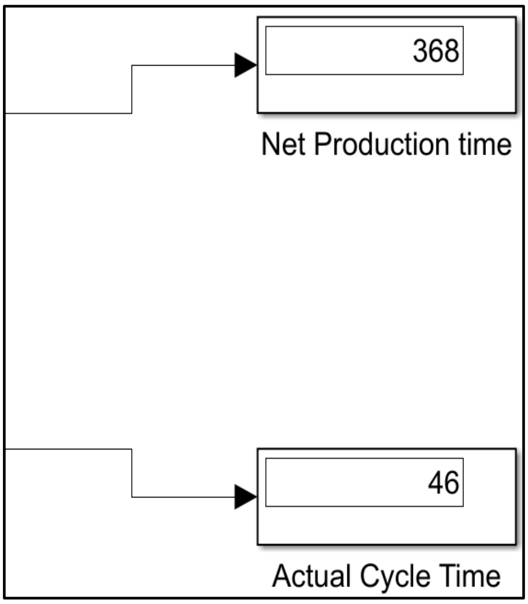

Figure 4.7: Digital Shadow calculated cycle time

The Digital Twin model uses the live data from the two IR sensors to calculate the value of cycle time. However, a Digital Twin provides a more detailed observation as the model can show the exact time the bottles take on SMU-1 and SMU-2, the net production time and cycle time of the 500ml bottles and of the 330ml bottles, and then the actual net production time and cycle time in the stochastic nature of the plant, as shown in Figure 4.8.

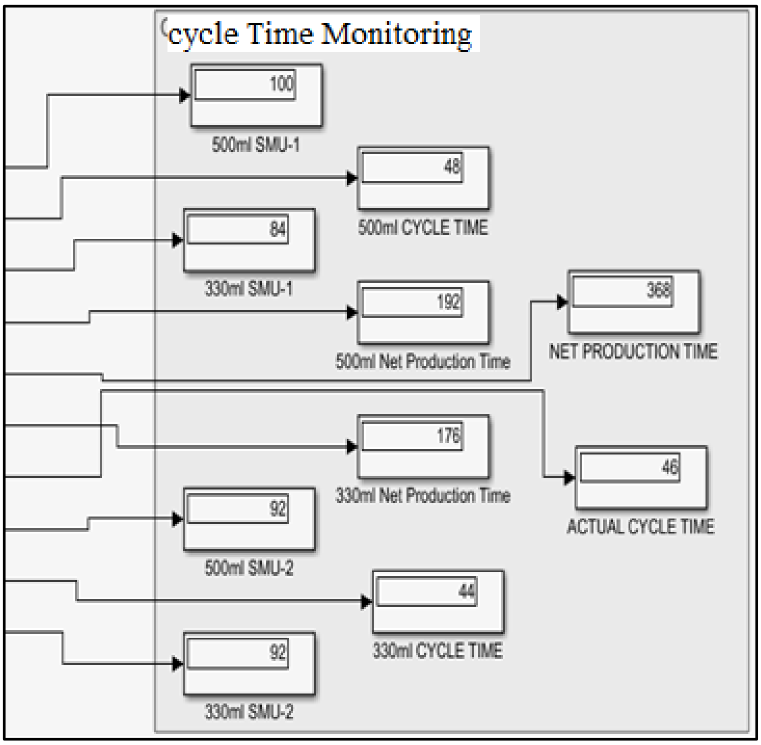

Figure 4.8: Digital Twin calculated cycle time

The value of cycle time in this example is the same for both models. This is due to the relatively smaller number of 500ml and 330ml bottles that were ordered. The Digital Shadow and Digital Twin models in this study will be compared in the next section, with a high number of orders to showcase which model is more suitable for calculating cycle time in a stochastic system.

4.6 Digital Shadow and Digital Twin Comparison

This section looks at the performance of the Digital Shadow and Digital Twin, in a mixed-model stochastic system. The two models were given the same set of customer orders as inputs to run tests and simulations in order to calculate the cycle time. The models are compared based on their results, and conclusions are drawn as to which model can reduce the cycle time more efficiently and thereby keep production efficient. Since this is a stochastic system, the orders were in no particular order. Table 4.2 shows the results that were obtained from the first set of customer orders by the two digital models.

Table 4.2: First customer set

Customer	Water Level	No. of 330ml bottles	No. of 500ml bottles	Digital Shadow Cycle Time(s)	Digital Twin Cycle Time(s)
A	100%	4	4	46	46
B	< 100% but > 75%	4	3	45.71	45.71
C	< 75% but > 50%	7	7	53.5	46
D	< 75% but > 50%	9	10	55.18	46.35
E	< 50% but > 25%	6	8	63.43	46.29
F	100% (refilled after E)	11	11	68.5	46
Total		41	43	332.32	276.35

After the completion of order E, the water level was below 25% and not enough to process the next order. Therefore, the tank needed to be refilled and the refilling time was 45 seconds, as discussed in Table 3.2 of Section 3.3. However, it should be noted that this only applies to the Digital Shadow, as the Digital Twin alerts the operator as soon as the water level is below 50% through the Digital Twin dashboard. Therefore, there are no pauses to the production in the Digital Twin, as the tank can be refilled while production is taking place.

The first set consists of six customised customer orders and shown in Figure 4.9 is the Digital Shadow model showing the calculated net production time and cycle time of the final customer order of set number one, with eleven 500ml bottles and eleven 330ml bottles being used as inputs to the model. This is how the cycle time is calculated for all the orders by the Digital Shadow.

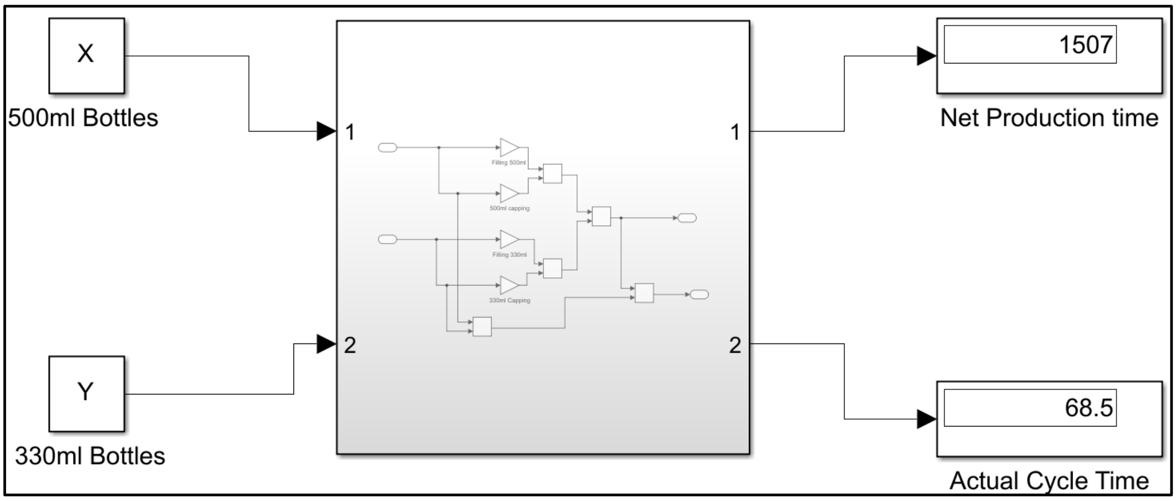

Figure 4.9: Digital Shadow model cycle time calculation

Unlike in the Digital Shadow model, the Digital Twin model uses the real-time data from the IoT sensors as inputs and therefore there are no pauses required in the production process. Instead, the Digital Twin is programmed to alert the operator(s) when the water level drops below 50% without stopping production, as discussed in Section 3.3.

The Digital Twin model, particularly, uses the real-time data from the two IR sensors as inputs to calculate the net production time and the cycle time, as shown in the Digital Twin model in Figure 4.11. Figure 4.10 shows the "WATER BOTTLING PLANT" *ThingSpeak* channel populated with the data from the IoT sensors. The data shown in the four fields of the channel is for the final customer order. It is seen that before the final order was processed, the water level was at 42cm (which is below 25%) and the operator had to refill the tank before the next order was affected.

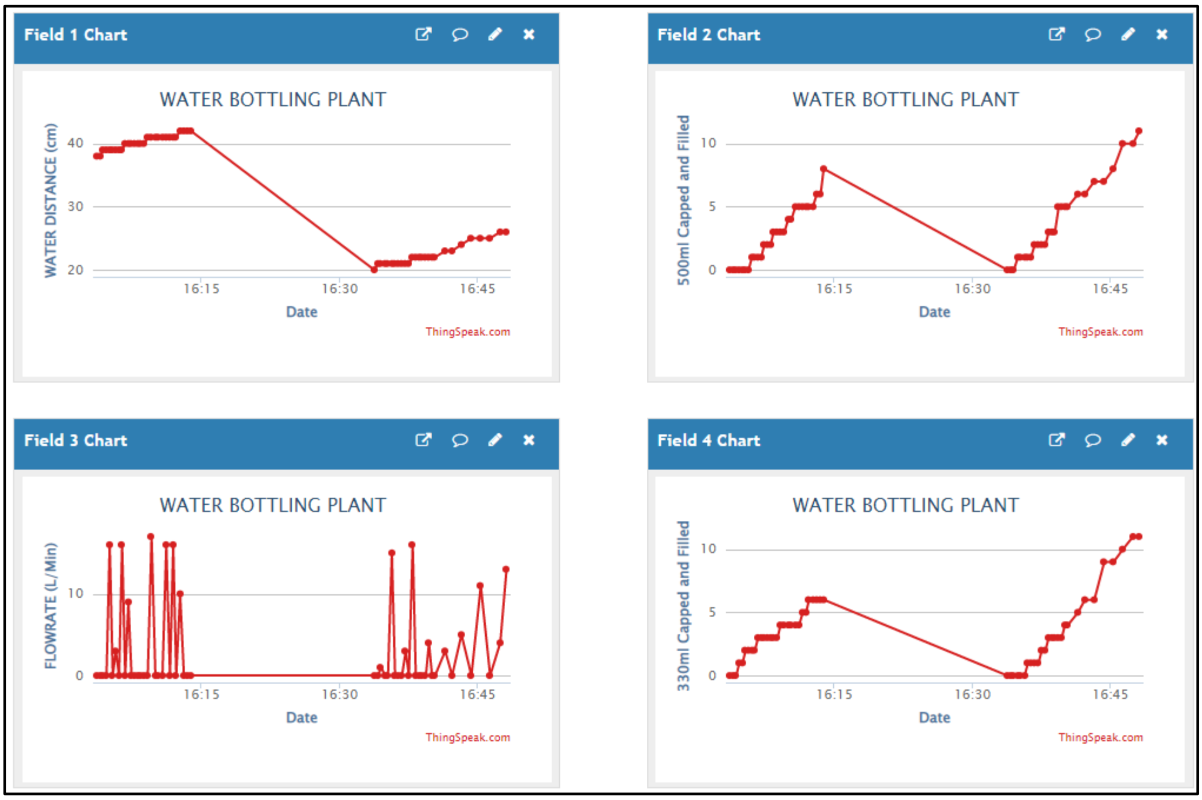

Figure 4.10: Data from the sensors during customer orders

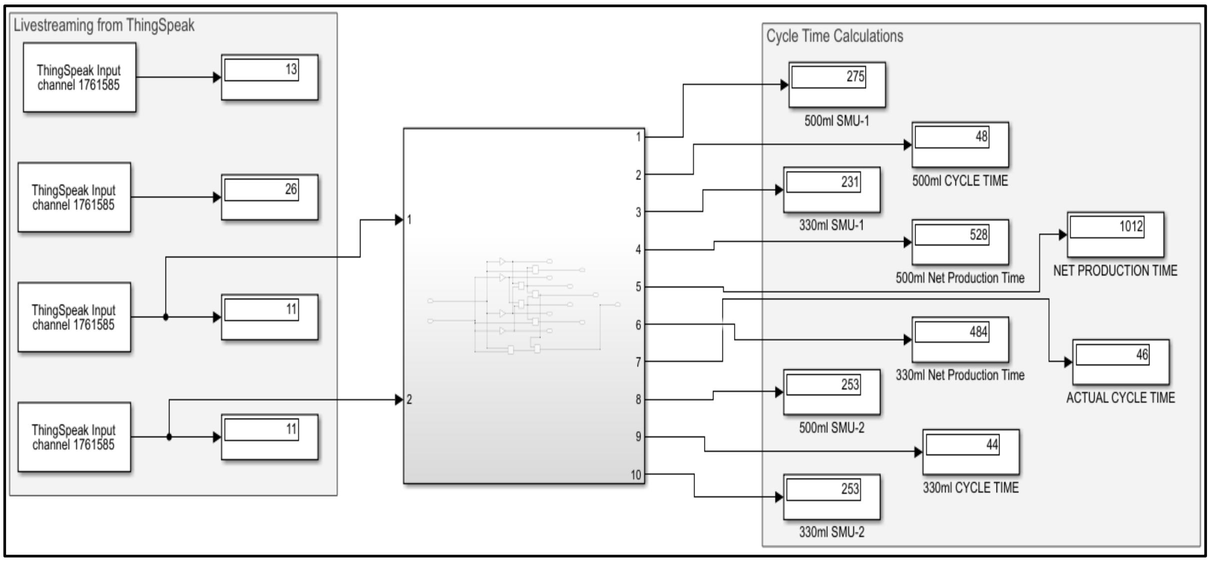

Figure 4.11: Digital Twin model used to calculate the cycle time

The data from the *ThingSpeak* channel fields is displayed on the Digital Twin's dashboard for simplified visualisation, as shown in Figure 4.12. The data that is displayed on this dashboard is for the final customer order of the first customer set, as there are eleven 500ml and 330ml bottles completed, respectively, the water level is at 26cm, and the water flowrate is 13L/min. This data matches that in the *ThingSpeak* channel shown in Figure 4.10.

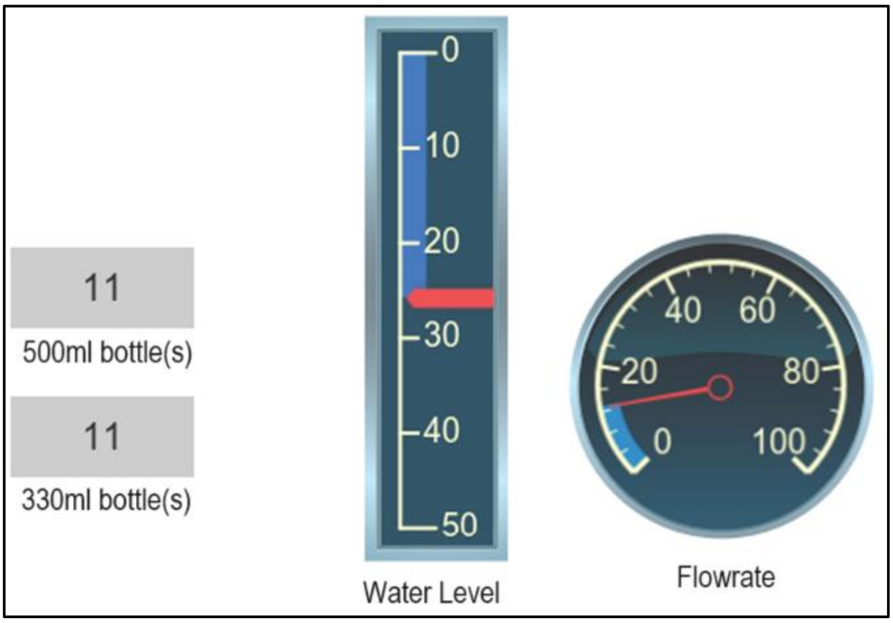

Figure 4.12: Order F data displayed on the dashboard

A total of six customer orders was received, where a total of 84 bottles were produced in the first set, 41 bottles being 330ml bottles and 43 being 500ml bottles. Figure 4.13 shows a comparison between the Digital Shadow and the Digital Twin models, which were used for testing and running simulations to calculate the cycle time.

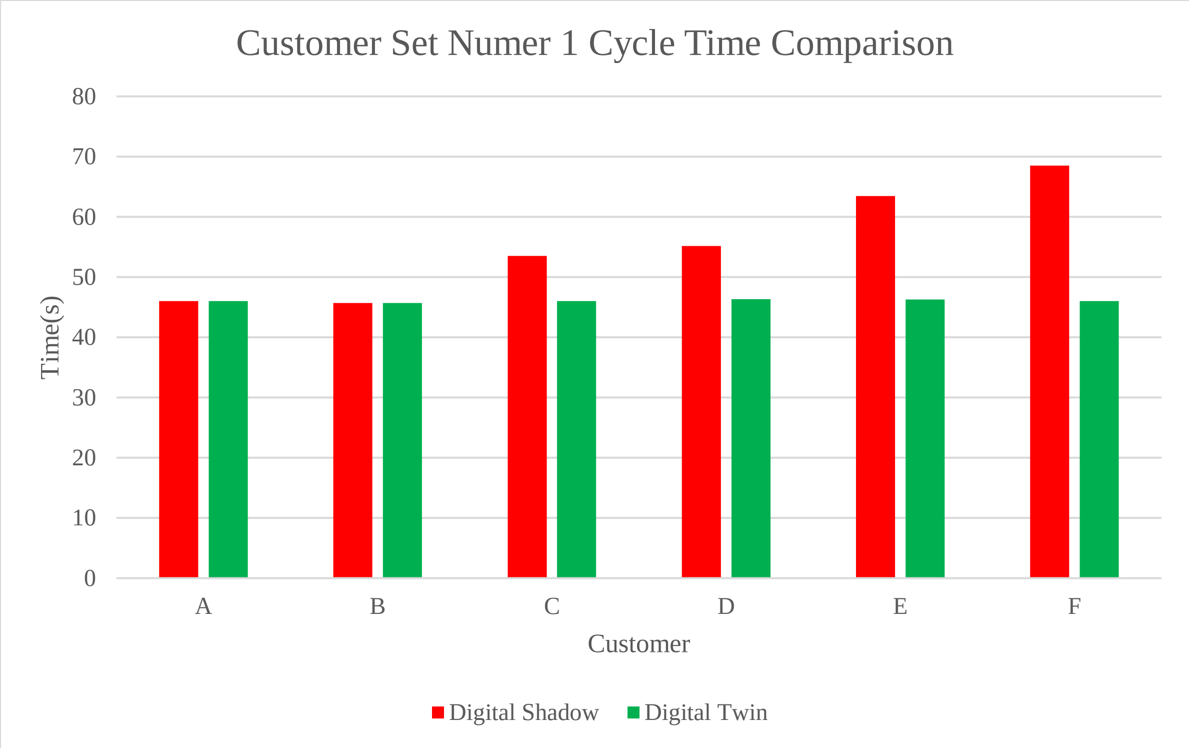

Figure 4.13: Customer set number 1 cycle time comparison

It is seen that during the initial stages of production, when the water level is still above 75%, the Digital Shadow and the Digital Twin provide the same cycle time. However, when the water drops below 75%, the Digital Shadow fails to keep up with the Digital Twin as the Digital Twin has the advantage of using real-time data as inputs and therefore can avoid bottlenecks and keep the production efficient.

A second set of customer orders, which are in a descending order, were received and used as inputs to the Digital Shadow and Digital Twin models and the results are as shown in Table 4.3. The results show that after customer Order A, the water tank had to be refilled, otherwise there would not be enough to process Order B. The same applies to the refilling after Order C.

Table 4.3: Second customer set

Customer	Water Level	No. of 330ml bottles	No. of 500ml bottles	Digital Shadow Cycle Time(s)	Digital Twin Cycle Time(s)
A	100%	20	20	46	46
B	100% (Refilled to process B)	17	17	61	46
C	< 75% but > 50%	15	15	53.5	46
D	100% (Refilled to process D)	10	10	68.5	46
E	< 75% but > 50%	7	7	53.5	46
F	< 75% but > 50%	2	2	53.5	46
Total		69	69	336	276

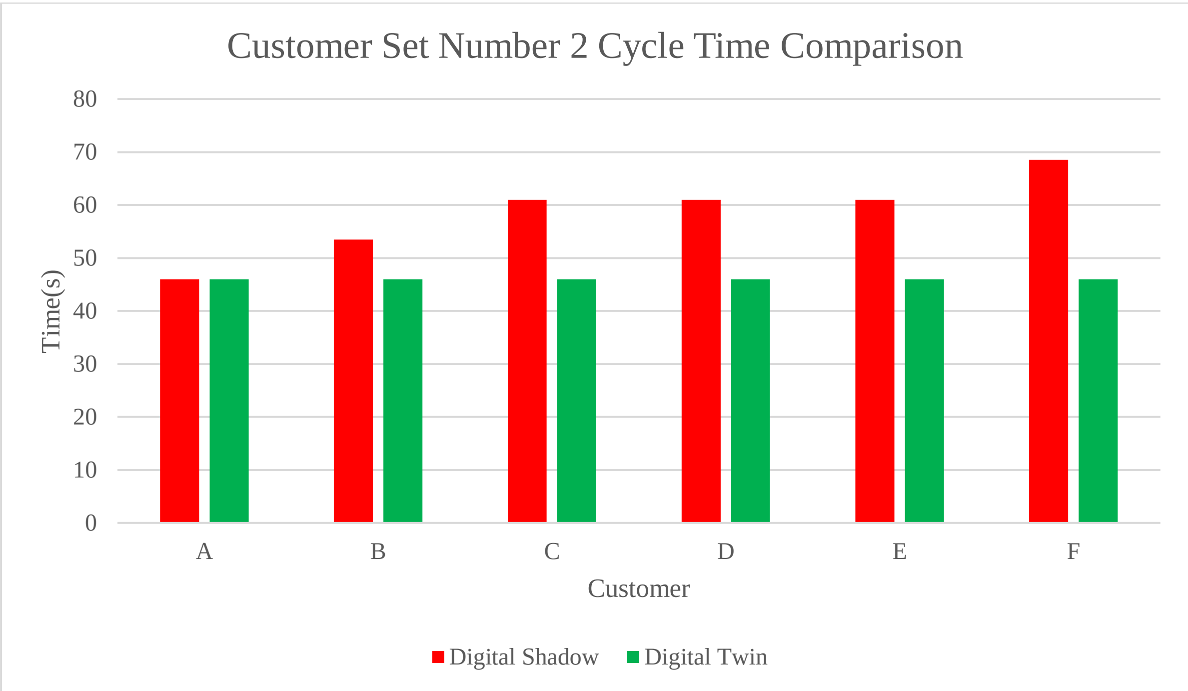

Figure 4.14: Customer set number 2 cycle time comparison

The third set of customer orders was received, as shown in Table 4.4, with the customer orders being in an ascending order for the 330ml water bottles and in a descending order for the 500ml water bottles. The results show that the water tank was refilled during the processing of Order C, as the water would not be enough to process the next order, which is Order D.

Table 4.4: Third customer set

Customer	Water Level	No. of 330ml bottles	No. of 500ml bottles	Digital Shadow Cycle Time(s)	Digital Twin Cycle Time(s)
A	100%	4	20	47.33	47.33
B	< 75% but > 50%	7	17	57.46	46.83
C	100% (Refilled to process C)	10	15	64.4	46.4
D	< 75% but > 50%	15	10	51.6	45.6
E	< 50% but > 25%	17	7	53.92	45.17
F	100% (Refilled to process C)	20	2	48.45	44.36
Total		73	71	323.16	275.69

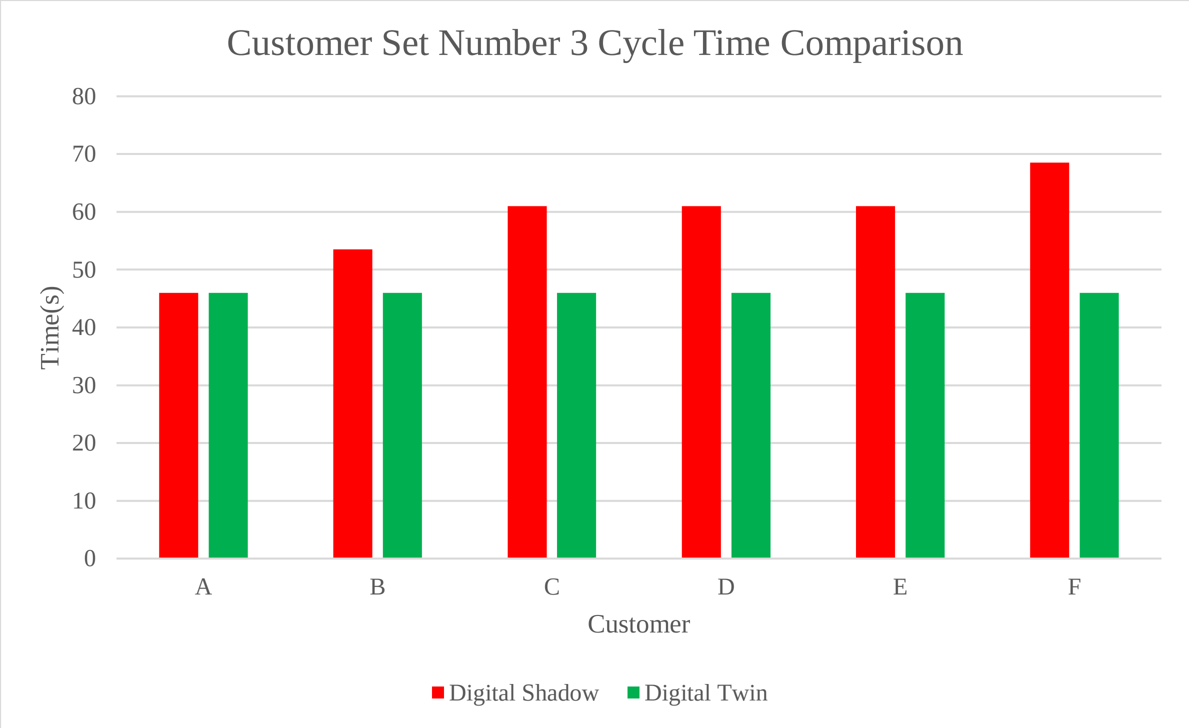

Figure 4.15: Customer set number 3 cycle time comparison

The fourth set of customer orders was received, as shown in Table 4.5, with the customer orders being in a descending order for the 330ml water bottles and in an ascending order for the 500ml water bottles. The results show that the water tank was refilled during the processing of Order C, as the water would not be enough to process the next order, which is Order D. The same applies in Order E, before processing Order F.

Table 4.5: Fourth customer set

Customer	Water Level	No. of 330ml bottles	No. of 500ml bottles	Digital Shadow Cycle Time(s)	Digital Twin Cycle Time(s)
A	100%	20	2	44.36	44.36
B	< 75% but > 50%	17	7	49.54	45.17
C	< 50% but > 25%	15	10	57.6	45.6
D	100% (Refilled to process D)	10	15	73.4	46.4
E	< 75% but > 50%	7	17	57.46	46.83
F	100% (Refilled to process F)	2	20	74.91	47.64
Total		71	71	357.27	276

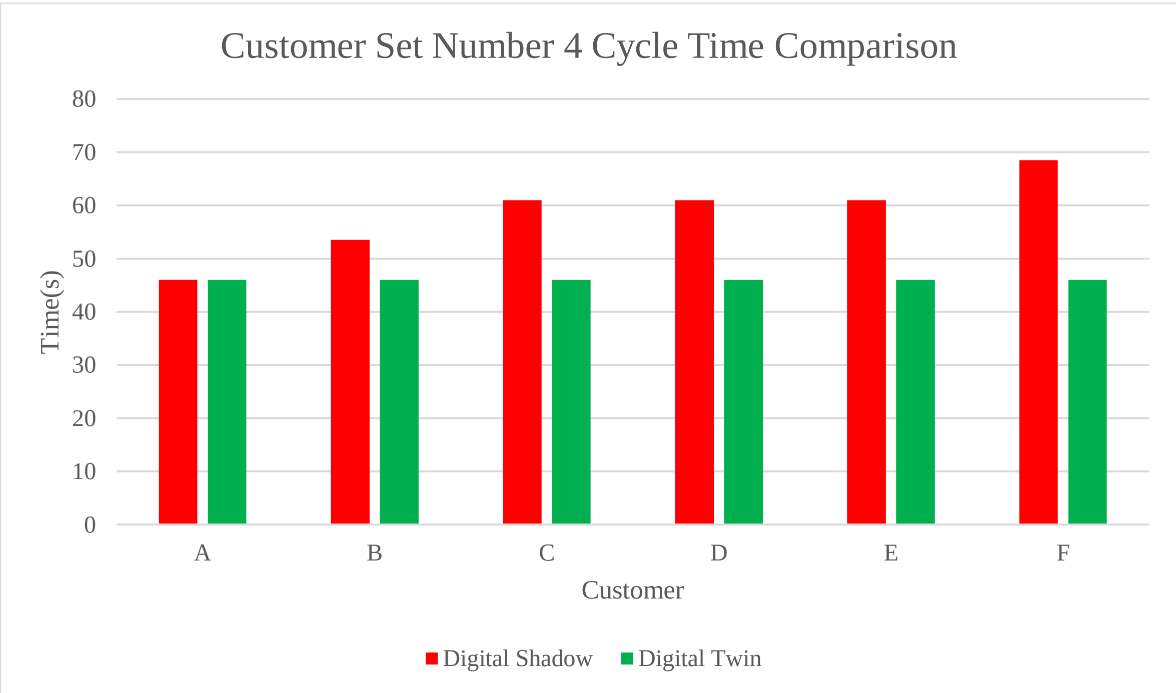

Figure 4.16: Customer set number 4 cycle time comparison

The fifth and final set of customer orders was received. In this set, the orders of both the 330ml and 500ml bottles were in an ascending order. However, the orders in this set were of a much higher quantity and, therefore, there was more refilling throughout the orders compared to the other customer sets, as seen in Table 4.6.

Table 4.6: Fifth customer set

Customer	Water Level	No. of 330ml bottles	No. of 500ml bottles	Digital Shadow Cycle Time(s)	Digital Twin Cycle Time(s)
A	100%	10	10	46	46
B	< 75% but > 50%	15	15	53.5	46
C	100% (Refilled to process C)	20	20	61	46
D	100% (Refilled to process D)	25	25	61	46
E	100% (Refilled to process E)	30	30	61	46
F	100% (Refilled to process F)	35	35	68.5	46
Total		135	135	351	276

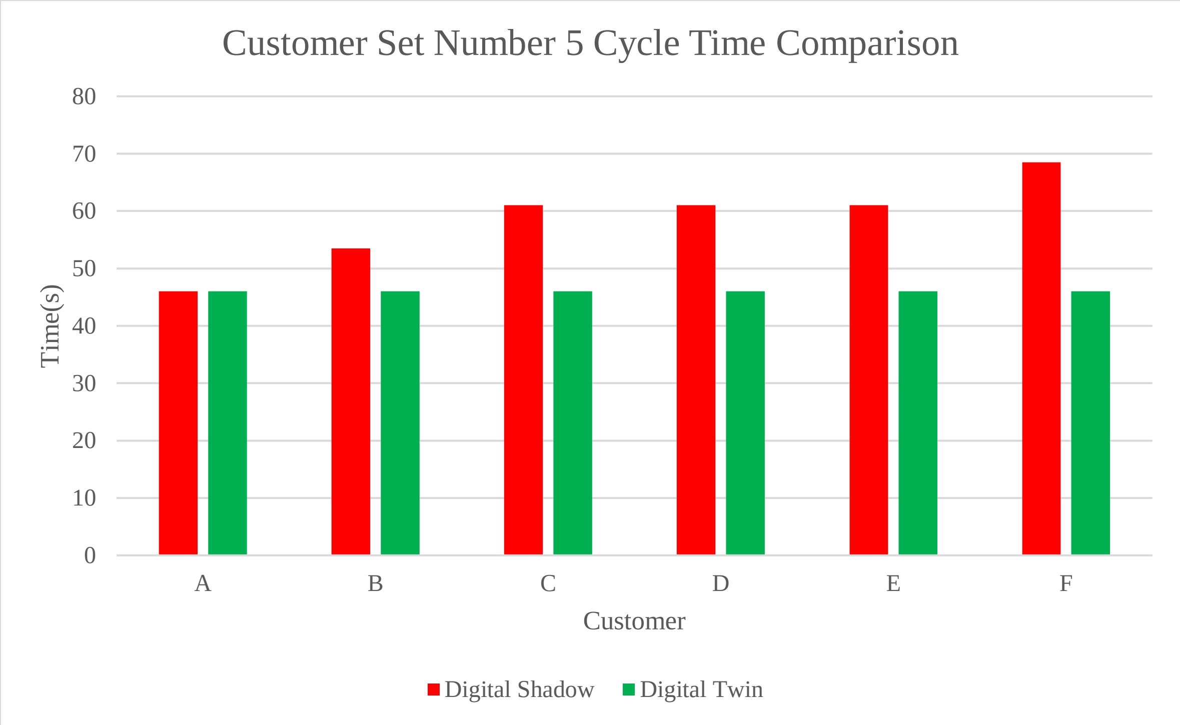

Figure 4.17: Customer set number 5 cycle time comparison

A total number of five customer sets, with six customer orders each, was received and processed in a mixed-model stochastic system. The five sets were used as inputs in both the Digital Shadow and the Digital Twin, and the results based on overall performance are depicted in Table 4.7.

Table 4.7: All customer sets

Customer set	No. of 330ml bottles	No. of 500ml bottles	Digital Shadow Cycle Time(s)	Digital Twin Cycle Time(s)
1	41	43	332.32	276.35
2	69	69	336	276
3	73	71	323.16	275.69
4	71	71	357.27	276
5	135	135	351	276
Total	389	389	1699.75	1380.04

A total number of five customer sets was received and processed, where a total of 778 water bottles were produced (389 being 330ml bottles and 389 being 500ml bottles). Figure 4.18 shows the overall cycle time performance of the Digital Shadow and the Digital Twin through the production of the 778 water bottles. Table 4.7 shows that the Digital Twin was more effective in cycle time reduction, with the cycle time improvement of 19% in overall performance, as compared to the Digital Shadow.

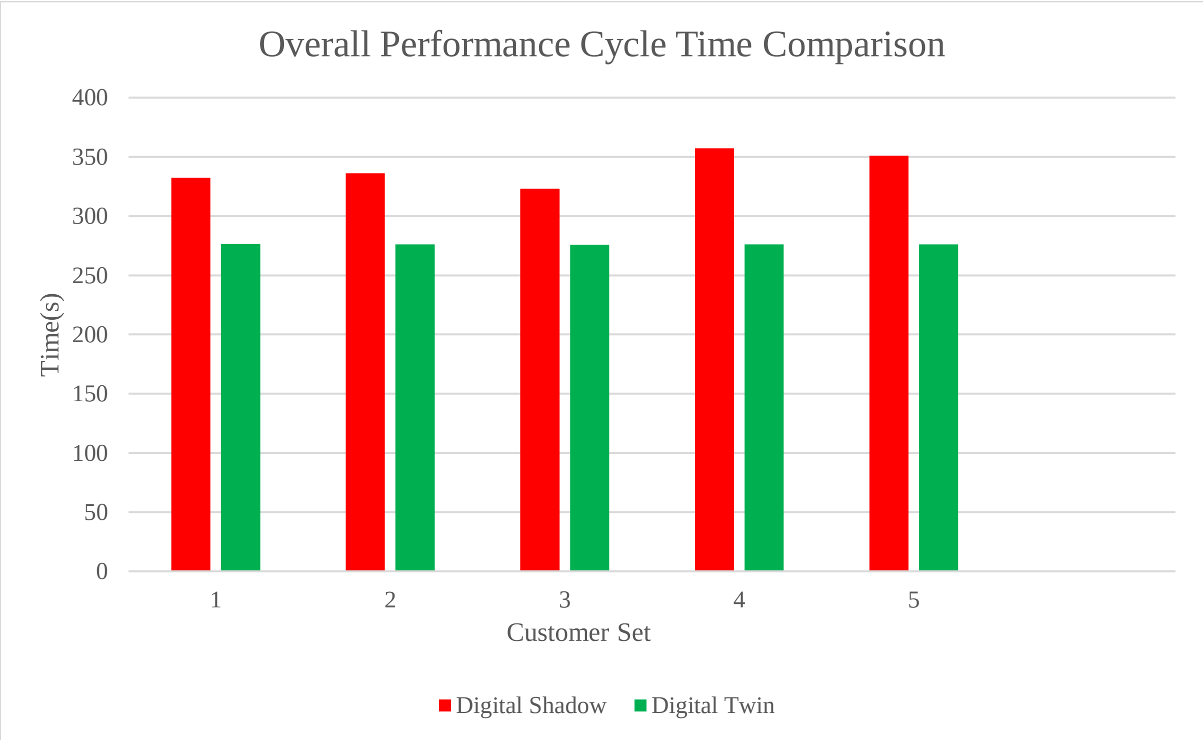

Figure 4.18: Overall performance cycle time comparison

4.7 Chapter conclusion

The focus in Chapter 4 was on presenting the results acquired from the tests and experiments conducted, using customer orders as inputs to the Digital Shadow and Digital Twin models developed in Chapter 3 to determine the cycle time. The chapter first presented the results of the Digital Shadow model. Next, the results of the real-time data collection system, which sets up the Digital Twin model, were shown. Finally, the comparison between the results of the Digital Shadow and Digital Twin model were presented. Based on the comparison results, it is evident that the Digital Twin model is a more suitable model for reducing the cycle time and enhancing productivity in a manufacturing setup, as compared to the Digital Shadow model.

In the next chapter, Chapter 5, the Digital Shadow and the Digital Twin models will be compared to the existing methods, based on the results acquired in Chapter 3. The aim is to showcase the reasoning behind the selection of the Digital Shadow as a competitor instead of the existing methods.

Chapter 5: Discussion

5.1 Introduction

This chapter discusses how the research gap identified in Section 2.7 has been filled through this study. The chapter does so by reviewing and discussing the results of the conducted experiments/tests of the previous chapter. Based on the results of the developed Digital Twin model, a comparison is made between the model and the existing techniques in the manufacturing industry.

5.2 Comparison between the developed model and the existing methods

The aim of this study was to develop a real-time data-driven Digital Twin model for a mixed-model assembly line to monitor process flow and reduce the cycle time, thereby optimising production. To fulfil the aim of this study, firstly, a real-time data collection system needed to be implemented, then integrated into the physical system after the selection of suitable sensors, thereby forming a data collection system.

Secondly, a cloud platform which is compatible with the microcontroller used in the real-time data collection system was selected for data storage. Lastly, the Digital Twin model was designed and developed after the Digital Shadow model, which then livestreams the real-time data stored in the cloud and uses it as inputs to determine the cycle time.

The test results indicate the developed data-driven Digital Twin model as more efficient in production optimisation. Table 5.1 summarises the comparison between the developed Digital Twin model, the existing methods, and with the developed Digital Shadow model as the main competitor. The developed Digital Twin model allows real-time inputs, has a low latency, can solve complex large-scale problems and is cost-effective.

The current challenges when balancing an assembly line and the lack of research in cycle time reduction, specifically mixed-model stochastic assembly lines, is what necessitated this study. It was established in the literature review that a mixed-model stochastic assembly line accentuates the line balancing problem resulting in an increased cycle time. Section 2.5 identified and detailed the techniques that are currently used in assembly lines to reduce the cycle time, along with their respective drawbacks.

Section 2.7 discussed the studies done using the techniques mentioned in Section 2.5, which then highlighted that there is very little existing research in cycle time reduction in the manufacturing industry at the time of writing this thesis, specifically where there are mixed/multi-model stochastic assembly lines, and the few studies that have focused on cycle time reduction do not use real-time data as input.

As discussed in Section 2.7, waste was eliminated and traced in a production line using Lean Manufacturing developed by Vijayakumar *et al.* [71] with the aim to reduce cycle time. However, Lean Manufacturing systems have a very high latency, due to lack of real-time inputs, which often slow the system down [72]. The developed Digital Twin model overcomes this factor by enabling real-time inputs which then result in very low latency.

Heuristics and meta-heuristics were used by Aguilar *et al.* [121] in a parallel assembly line with multiple workstations and different cycle times to solve a buffer sizing problem. Meta-heuristics provide much improved solutions as compared to heuristics [81]. However, the latency is very high in meta-heuristics, as compared to heuristics [81]. The drawback of heuristics approaches was that they do not produce satisfactory results when dealing with large-scale problems such as those encountered in the case of Mixed-Model Assembly Line Balancing Problem (MALBP), Mixed-Model Sequencing Problem (MSP), and U-shaped Assembly Line Balancing Problem (UALBP) [126].

The developed Digital Twin model overcame the limitations of heuristics and meta-heuristics by allowing real-time inputs, as the heuristics and meta-heuristics do not use real-time inputs. Therefore, the latency in the Digital Twin is very low. The Digital Twin model was developed for reducing the cycle time in a mixed-model stochastic assembly line, making it a solution for large-scale problems that heuristics fail to overcome.

A Digital Twin was developed for a parallel assembly line in a closed-loop manufacturing system which has a stochastic processing time and is made up of five workstations, to predict the remaining cycle time in a study by Lugaresi *et al.* [122]. The Digital Twin model in this study varies from the one by Lugaresi *et al.* [122] in that it was developed for a mixed-model stochastic system for cycle time reduction.

This research study developed a real-time data-driven Digital Twin model and a Digital Shadow model to test, analyse and compare the cycle time. The models received five customer sets of orders, each set containing six different customer orders, to process and calculate the manufacturing cycle time. This was done to prove the stochasticity of the system. The first customer set of orders was in an ascending order; the second set was in a descending order; in the third set, the 330ml bottles were in an ascending order, and the 500ml bottles in a descending order; in the fourth set, the 330ml bottles were in a descending order and 500ml bottles in an ascending order, and in the fifth and final customer set, the bottles were in an ascending order.

To ascertain the veracity of the developed Digital Twin model, the results showcased a total of 778 water bottles that were produced (389 being 330ml bottles and 389 being 500ml bottles) from the conducted tests. It is evident from the results that cycle time reduction is the same for both models when the water level in the filling tank is above 75%. However, as soon as the water level drops below 75%, it was observed that the cycle time of the Digital Shadow is greater than that of the Digital Twin. This is because the inputs in the Digital Shadow model are not in real-time. Therefore, it is necessary to have some pauses in the production process, to allow the refilling. Meanwhile, in the Digital Twin model, the inputs are in real-time. Therefore, there exists no need for production pauses, as refilling can occur while production is ongoing. The overall performance thus proves and validates the Digital Twin model to be efficient at cycle time reduction, with an improvement of 19% reduction in cycle time, compared to when using a Digital Shadow.

Table 5.1 shows a comparison between the developed Digital Shadow and Digital Twin models against the existing methods, in a manufacturing industry context. The table shows that the developed Digital Shadow and Digital Twin models are more efficient, as compared to the existing methods. However, it is also evident that the capability to take in real-time inputs makes the Digital Twin superior as compared to the Digital Shadow.

Table 5.1: Comparison between the developed model and existing methods

	Lean Manufacturing [71]	Heuristics [121]	Meta-heuristics [120]	Digital Shadow	Digital Twin
Real-time Inputs	No	No	No	No	Yes
Latency	High	Low	High	Low	Low
Large-scale problems	No	No	Yes	Yes	Yes
Minimise costs	Yes	Yes	Yes	Yes	Yes

5.3 Research Contributions

This research study developed a data-driven Digital Twin for a mixed-model assembly line for the reduction of cycle time. The following contributions from the study are considered to be novel.

5.3.1 Contribution to existing knowledge

To gain in-depth understanding on assembly line balancing, several journal articles were studied in this research study and specifically Eghtesadifard *et al.* [127]. In this article, updates performed within the assembly line balancing field from the year 2000 to 2018 were captured. As part of contribution to new knowledge, a journal article [97] titled "*Analyzing the Performance of a Digital Shadow for a Mixed-Model Stochastic System*" was published in 2022. This article analysed the performance of the Digital Shadow in a mixed-model stochastic production line and highlighted the need for real-time inputs.

The next journal article [90] titled "*Designing an Experimental Setup for Digital Twins in Modern Manufacturing—A Case Study Using a Water Bottling Plant*" was published in 2023. This contributed new knowledge by developing an experimental setup of a Digital Twin in mixed-model stochastic assembly line. Another journal article [72] titled "*Integrating IoT Sensors to Setup a Digital Twin of a Mixed Model Stochastic System for Real-Time Monitoring*" was published in 2023. This article contributed new knowledge by focusing on the integration of IoT sensors in a mixed-model stochastic system to set up a real-time data-driven Digital Twin.

The results of this research study were presented at the 9th International Congress on Information and Communication Technology (ICICT), 2024, in a conference paper titled "*A Performance Comparison between a Digital Shadow and a Digital Twin in a Mixed Model Stochastic System*".

5.3.2 Development of a data-driven Digital Twin model

The inability of the existing methods to take real-time data as input necessitated the development of the Digital Twin model for the mixed-model stochastic assembly line. The Digital Twin model developed is a replica of the mixed-model stochastic assembly line presented in a digital format (on SIMULINK). The integrated sensors enable the Digital Twin model to use both historical and real-time data to make necessary predictions.

This would mean that the developed Digital Twin model can be used as basis for future studies in mixed/multi-model stochastic assembly lines and in other fields which require a data collection system. Therefore, experiments and tests can be conducted without any structural changes and without the requirement of new optimisation toolboxes.

5.3.3 Contributions to Industry 4.0

Industry 4.0 offers a wide range of new emerging technologies to better the future of manufacturing. These technologies include Cyber Physical Systems (CPS), Artificial Intelligence (AI) and Internet of Things (IoT), to name a few, to drive Smart Manufacturing (also known as Smart Factories). The Digital Twin model developed in this study comprised the IoT technology for data collection purposes.

5.4 Chapter Conclusion

The focus in Chapter 5 was on discussing, in summary, the results obtained from this study. The aim was to ensure that all research gaps identified as problem statement were filled. This was achieved by comparing the developed solution with the existing methods.

Chapter 6: Conclusion

6.1 Introduction

This chapter aims at highlighting the contributions of this study to existing research. To conclude this study, the research aims and objectives are revisited. A summary of the results achieved also forms part of this chapter.

6.2 Summary

The first chapter introduced the modes of operation used in manufacturing, and which modes are compatible with the Fourth Industrial Revolution (Industry 4.0) and the demands of the ongoing market. The research project was introduced in the first chapter, as well as the problem the research aimed to solve. Then, the research hypothesis was identified, and a list of research objectives were stated, from which the methodology of the research followed. The first chapter was concluded by looking at the layout of the dissertation.

In the second chapter, the literature review was conducted in depth. This was done by initially focusing on the generalised problem of assembly line balancing and identifying the challenge. The chapter also introduced and looked at the concept of Digital Twins, and how Digital Twins are a possible solution to the stated problem. The chapter concluded by looking at the limitations of the existing research in the field that relate to this specific topic.

In the third chapter, the focus was on the research methodology used to develop a data-driven Digital Twin as a solution to the problem. This chapter initially discussed the water bottling plant case study and why it was selected for this study. This chapter also showcased how the Digital Twin model of the Make-to-Order water bottling plant was designed and developed using the *MATLAB* and *SIMULINK* platforms.

The fourth chapter consisted of a detailed analysis and depicted the results of the research methodology used to develop the Digital Twin model. This was done by first describing the data from the experiment conducted to develop the primary model, the Digital Shadow, followed by the secondary model, the Digital Twin model, and then the collected data from the sensors. Thereafter, a cycle time performance comparison between the primary and the secondary model, as model validation, was conducted.

6.3 Research Goals

The main goal of this research was to reduce the cycle time in a mixed-model stochastic assembly line by monitoring the process flow in real-time, thereby improving efficiency. However, this posed a number of challenges as the existing systems are simulation-based and do not operate with real-time inputs.

Therefore, to study this unique problem, a comprehensive review on literature focusing on assembly line balancing needed to be done. Secondly, a data-driven Digital Twin model for the water bottling plant case study was designed and developed using the *MATLAB* and *SIMULINK* platforms to conduct tests and experiments. Thirdly, a cloud platform that is compatible with the real-time data collection system of the model was selected. This would allow real-time data to be provided to the model as inputs. Next, the model was used to conduct tests related to cycle time. This step paved the way for the formulation of the cycle time problem by identifying conceivable constraints. Finally, a comparison was done between the Digital Shadow model and the Digital Twin model in relation to cycle time.

The literature review was conducted in Chapter 2. It focused initially on assembly line balancing and the assembly line classification. The chapter then went on to discuss the problems associated with assembly line balancing. In Section 2.4, the factors that affect the production time were discussed and the importance of cycle time reduction was highlighted and detailed, which was the problem this study focused on. This chapter also provided a comprehensive discussion on the assembly line balancing techniques that are currently used to reduce the cycle time and the limitations of existing research. The limitations of existing research stimulated the need for the study as stated in the problem statement.

As mentioned previously, a case study was selected to demonstrate the experimental setup of the data collection system of the Digital Twin model. The data needed to be collected, processed, stored and used as input to the Digital Twin model. This was done in Chapter 3. Here, a case study of a water bottling plant was selected. The bottling plant can produce a variety (330ml and 500ml bottles) of the same product, making the bottling plant an example of a mixed-model stochastic assembly line, hence the selection of this case study. Section 3.3 detailed the experimental setup. Section 3.4 detailed the design and development of the Digital Shadow model (the primary model) on *SIMULINK*. The primary model then used real-time data as inputs, converting the model into a Digital Twin model (the secondary model). This was discussed in Section 3.5. This chapter concluded by monitoring the different cycle time calculations from the models.

The results of the research study were collated in a structured manner. This was done in Chapter 4. Here, a series of test experiments was initially conducted to determine the times it took each bottle in the two different SMUs (Smart Manufacturing Units) that made up the primary model. This was discussed in Section 4.2. Next, the results of the data collection system were portrayed, followed by data processing and cycle time calculation results. Section 4.6 showed the comparison results between the Digital Shadow and the Digital Twin models using the same set of customer orders as inputs.

The chapter was concluded by ascertaining the veracity of the Digital Twin model. A total of five customer sets were received, in various sequences. The customer sets were provided to the developed Digital Shadow and Digital Twin models as input, to optimise production by reducing the cycle time. Each set was provided with six different customers where close to 800 water bottles were produced in total. The results showed that both the Digital Shadow and Digital Twin models were successful in reducing the manufacturing cycle time and therefore optimising production. However, in instances where the water level was is below 75%, the Digital Shadow model’s performance was not satisfactory. This was because the inputs into the Digital Shadow model were not in real-time and therefore resulted in some delays to the production process. It is evident that the ability to use real-time data as input makes the Digital Twin model a more suitable model for production optimisation, as the monitoring of raw materials is in real-time and therefore the refilling can occur while production is ongoing.

6.4 Recommendations and Future Work

This dissertation is presented as part of the ongoing research project conducted by the Central University of Technology (CUT), Free State, focusing on various Assembly Line Balancing Problems and how assembly lines can be optimised by reducing the manufacturing cycle time to enhance production.

The conclusions in this study provide a platform for more studies to be launched, extending from the findings in this study. The focus of this study was on cycle time reduction in a mixed-model stochastic assembly line. However, other types of assembly lines and their objectives can and should also be explored.

The data-driven Digital Twin model developed in this study can be further used to formulate more studies. The first aspect for further studies will be to use the real-time data collection system of the Digital Twin model to develop a Model Predictive Controller (MPC) that can use the data collected to predict downtime in a South African manufacturing industry, based on the loadshedding schedule. This will help in reducing both the company costs and lead-time, and therefore improve productivity.

Another possible extension to this study will be to design and develop a data-driven Digital Twin model for predictive maintenance in last-mile delivery drones, since the advent of Industry 4.0 has brought an increase in the use of e-commerce. A new real-time data collection system will be set up, after the identification and selection of sensors that are compatible with the selected microcontroller. This will enable real-time monitoring of the drone's electronic components and therefore predictions can be made as to when components need to be replaced, in turn minimising both the costs and the maintenance time.

6.5 Scientific Outcomes

- P. Tshabalala and R. B. Kuriakose, "Analyzing the Performance of a Digital Shadow for a Mixed-Model Stochastic System," in *Lecturer Notes in Networks Systems*, vol. 461, Harish Sharma, Ed., Singapore: Springer, 2022, pp. 651–660. [Online]. Available: https://doi.org/10.1007/978-981-19-2130-8_50

- P. Tshabalala and R. B. Kuriakose, "Designing an Experimental Setup for Digital Twins in Modern Manufacturing—A Case Study Using a Water Bottling Plant," *Lecture Notes in Networks and Systems*, vol. 516, pp. 615–622, 2023, doi: 10.1007/978-981-19-5221-0_58.

- P. Tshabalala and R. B. Kuriakose, "Integrating IoT Sensors to Setup a Digital Twin of a Mixed Model Stochastic System for Real-Time Monitoring," *Lecture Notes in Networks and Systems*, vol. 693, pp. 311–319, Jul. 2023, [Online]. Available: https://link.springer.com/Chapter/10.1007/978-981-99-3243-6_24.

- P. Tshabalala and R. B. Kuriakose, "A Performance Comparison between a Digital Shadow and a Digital Twin in a Mixed Model Stochastic System," presented at the *9th International Congress on Information and Communication Technology (ICICT), 2024*, conference.

References

[1] H. Wicaksono and T. Ni, "An Automated Information System for Medium to Short-Term Manpower Capacity Planning in Make-To-Order Manufacturing," *Procedia Manuf*, vol. 52, no. 2019, pp. 319–324, 2020, doi: 10.1016/j.promfg.2020.11.053.

[2] D. Gupta and S. Benjaafar, "Make-to-order, make-to-stock, or delay product differentiation? A common framework for modeling and analysis," *IIE Transactions (Institute of Industrial Engineers)*, vol. 36, no. 6, pp. 529–546, 2004, doi: 10.1080/07408170490438519.

[3] J. Zenisek, N. Wild, J. Wolfartsberger, J. Zenisek, N. Wild, and J. Wolfartsberger, "Investigating the Potential of Smart Manufacturing Technologies," *Procedia Comput Sci*, vol. 180, no. 2019, pp. 507–516, 2021, doi: 10.1016/j.procs.2021.01.269.

[4] R. B. Kuriakose and H. J. Vermaak, "Customized Mixed Model Stochastic Assembly Line Modelling Using Simulink," *International Journal of Simulation- Systems, Science and Technology*, vol. 20, 2019, doi: 10.5013/IJSSST.a.20.S1.06.

[5] R. B. Kuriakose and H. J. Vermaak, "Optimization of a Real Time Web Enabled Mixed Model Stochastic Assembly Line to Reduce Production Time," *Advanced Informatics for Computing Research*, pp. 39–50, 2019, [Online]. Available: https://doi.org/10.1007/978-981-15-0108-1_5

[6] E. Álvarez-Miranda, J. Pereira, and M. Vilà, "A branch, bound and remember algorithm for maximizing the production rate in the simple assembly line balancing problem," *Comput Oper Res*, vol. 166, Jun. 2024, doi: 10.1016/j.cor.2024.106597.

[7] X. Zhu, "Modeling product variety induced manufacturing complexity for assembly system design," *ProQuest Dissertations and Theses*, 2009, [Online]. Available: https://deepblue.lib.umich.edu/handle/2027.42/62265

[8] N. Boysen, M. Fliedner, and A. Scholl, "Production planning of mixed-model assembly lines: Overview and extensions," *Production Planning and Control*, vol. 20, no. 5, pp. 455–471, 2009, doi: 10.1080/09537280903011626.

[9] X. Liu, X. Yang, and M. Lei, “Optimisation of mixed-model assembly line balancing problem under uncertain demand,” *J Manuf Syst*, vol. 59, no. September 2020, pp. 214–227, 2021, doi: 10.1016/j.jmsy.2021.02.019.

[10] A. S. Simaria and P. M. Vilarinho, “A genetic algorithm based approach to the mixed-model assembly line balancing problem of type II,” *Comput Ind Eng*, vol. 47, no. 4, pp. 391–407, 2004, doi: 10.1016/j.cie.2004.09.001.

[11] N. Kumar and D. Mahto, “Assembly Line Balancing: A Review of Fevelopments and Trends in Approach to Industrial Application,” *Global Journal of Research In Engineering*, vol. 13, no. 2, pp. 807–811, 2013.

[12] B. Lathashankar, G. Ashritha, S. Asma, K. Shivam, and K. Nitesh, “Cycle time reduction in manufacturing industry by designing a dedicated fixture: A case study,” *International Journal of Engineering, Science and Technology*, vol. 10, no. 3, pp. 34–42, 2018, doi: 10.4314/ijest.v10i3.4.

[13] H. Patel and S. C. Shah, “Review on Cycle Time Reduction in Manufacturing Industries,” *Journal of Emerging Technologies and Innovative Research (JETIR)*, vol. 1, no. 7, pp. 955–957, 2014.

[14] P. Tarasewich and P. R. McMullen, “Using ant techniques to solve the assembly line balancing problem,” *IIE Transactions*, vol. 35, pp. 605–617, 2003, doi: 10.1080/07408170390214473.

[15] X. Weida and T. Xiao, “Mixed model assembly line balancing problem with fuzzy operation times and drifting operations,” *Proceedings of the 2008 Winter Simulation Conference*, pp. 1752–1760, 2008, doi: 10.1109/WSC.2008.4736263.

[16] S. Matanachai and C. A. Yano, “Balancing mixed-model assembly lines to reduce work overload,” *IIE Transactions (Institute of Industrial Engineers)*, vol. 33, no. 1, pp. 29–42, 2001, doi: 10.1080/07408170108936804.

[17] P. Sivasankaran and P. M. Shahabudeen, "Heuristics for Mixed Model Assembly Line Balancing Problem with Sequencing," *Intell Inf Manag*, vol. 8, no. 3, pp. 41–65, 2016, doi: 10.4236/iim.2016.83005.

[18] R. Rosen, G. Von Wichert, G. Lo, and K. D. Bettenhausen, "About the importance of autonomy and digital twins for the future of manufacturing," *IFAC-PapersOnLine*, vol. 28, no. 3, pp. 567–572, 2015, doi: 10.1016/j.ifacol.2015.06.141.

[19] J. Leng, D. Wang, W. Shen, X. Li, Q. Liu, and X. Chen, "Digital twins-based smart manufacturing system design in Industry 4.0: A review," *J Manuf Syst*, vol. 60, no. March, pp. 119–137, 2021, doi: 10.1016/j.jmsy.2021.05.011.

[20] C. G. S. Sikora, "Balancing mixed-model assembly lines for random sequences," *Eur J Oper Res*, vol. 314, no. 2, pp. 597–611, Apr. 2023, doi: 10.1016/j.ejor.2023.10.008.

[21] R. Panchal, A. Awasare, and A. Zende, "Development of Assembly Line Layout for Measurement of Work," *International Advanced Research Journal in Science, Engineering and Technology*, vol. 4, no. 1, 2017, doi: 10.17148/IARJSET/NCDMETE.2017.40.

[22] N. Boysen, P. Schulze, and A. Scholl, "Assembly line balancing: What happened in the last fifteen years?," *European Journal of Operational Research*, vol. 301, no. 3. Elsevier B.V., pp. 797–814, Sep. 16, 2022. doi: 10.1016/j.ejor.2021.11.043.

[23] F. Pilati, G. Lelli, M. Faccio, M. Gamberi, and A. Regattieri, "Assembly line balancing for personalized production," *IFAC-PapersOnLine*, vol. 53, no. 2, pp. 10261–10266, 2020, doi: 10.1016/j.ifacol.2020.12.2758.

[24] G. Fan, H. Zheng, Z. Jiang, J. Liu, and S. Lou, "Multi-objective assembly line rebalancing problem based on complexity measurement in green manufacturing," *Eng Appl Artif Intell*, vol. 132, Jun. 2024, doi: 10.1016/j.engappai.2024.107884.

[25] Y. Y. Chen, P. Pourhejazy, and T. N. Liu, "Line balancing problem with multi-manned workstations and resource constraints: The case of electronics waste disassembly,"

Cleaner Logistics and Supply Chain, vol. 10, Mar. 2024, doi: 10.1016/j.clscn.2023.100129.

[26] A. Adeppa and M. S. Uppin, "An Overview of Assembly Line Balancing," *International Journal of Engineering and Innovative Technolog*, vol. 7, no. 8, pp. 38–42, 2018, doi: 10.17605/OSF.IO/BXU42.

[27] A. S. V. Raj, J. Mathew, P. Jose, and G. Sivan, "Optimization of Cycle Time in an Assembly Line Balancing Problem," *Procedia Technology*, vol. 25, pp. 1146–1153, 2016, doi: 10.1016/j.protcy.2016.08.231.

[28] Y. Zhai, G. Hua, M. Cheng, and T. C. E. Cheng, "Production lead-time hedging and order allocation in an MTO supply chain," *Eur J Oper Res*, vol. 311, no. 3, pp. 887–905, Dec. 2023, doi: 10.1016/j.ejor.2023.05.031.

[29] C. Li, T. Yu, H.-T. Fan, G. Xiao, J. Arinez, and Q. Chang, "Dynamic Bottleneck Identification and Production Loss Evaluation for Assembly Lines," *Manuf Lett*, vol. 35, pp. 1089–1096, 2023, [Online]. Available: https://doi.org/10.1016/j.mfglet.2023.08.089

[30] L. Belkharroubi and K. Yahyaoui, "Solving the mixed-model assembly line balancing problem type-I using a Hybrid Reactive GRASP," *Prod Manuf Res*, vol. 10, no. 1, pp. 108–131, 2022, doi: 10.1080/21693277.2022.2065380.

[31] S. E. A. El Ahmadi, L. El Abbadi, and M. T. Belghiti, "A review paper on algorithms used for simple assembly line balancing problems in the automotive industry," *Proceedings of the International Conference on Industrial Engineering and Operations Management*, pp. 1840–1846, 2019.

[32] Y. Delice, E. K. Aydoğan, S. Himmetoğlu, and U. Özcan, "Integrated mixed-model assembly line balancing and parts feeding with supermarkets," *CIRP J Manuf Sci Technol*, vol. 41, pp. 1–18, Apr. 2023, doi: 10.1016/j.cirpj.2022.12.002.

[33] P. Sivasankaran and P. Shahabudeen, “Literature review of assembly line balancing problems,” *The International Journal of Advanced Manufacturing Technology*, vol. 73, pp. 1665–1694, 2014, doi: 10.1007/s00170-014-5944-y.

[34] G. Belfiore, D. Falcone, and L. Silvestri, “Assembly line balancing techniques: Literature review of deterministic and stochastic methodologies,” *17th International Conference on Modeling and Applied Simulation, MAS 2018*, pp. 185–190, 2018.

[35] B. Vaisi, “A review of optimization models and applications in robotic manufacturing systems: Industry 4.0 and beyond,” *Decision Analytics Journal*, vol. 2, Mar. 2022, doi: 10.1016/j.dajour.2022.100031.

[36] B. Zhang, L. Xu, and J. Zhang, “Balancing and sequencing problem of mixed-model U-shaped robotic assembly line: Mathematical model and dragonfly algorithm based approach,” *Appl Soft Comput*, vol. 98, Jan. 2021, doi: 10.1016/j.asoc.2020.106739.

[37] Ágota Bányai, “DECISION MAKING IN OPERATOR-MACHINE ASSIGNMENT PROBLEMS: AN OPTIMIZATION APPROACH IN U-SHAPED PRODUCTION LINES,” *Applications in Management and Engineering*, vol. Vol. 6, no. 2, pp. 620–638, 2023, [Online]. Available: https://doi.org/10.31181/dmame622023808

[38] M. Alonge *et al.*, “Automated assembly scaffolding using RagTag elevates a new tomato system for high-throughput genome editing,” *Genome Biol*, vol. 23, no. 1, Dec. 2022, doi: 10.1186/s13059-022-02823-7.

[39] A. Miqueo, M. Torralba, and J. A. Yagüe-Fabra, “Lean manual assembly 4.0: A systematic review,” *Applied Sciences (Switzerland)*, vol. 10, no. 23. MDPI AG, pp. 1–37, Dec. 01, 2020. doi: 10.3390/app10238555.

[40] I. Dimény and T. Koltai, “Minimising workers’ workload in partially automated assembly lines with human-robot collaboration,” *IFAC-PapersOnLine*, vol. 55, no. 10, pp. 1734–1739, 2022, doi: 10.1016/j.ifacol.2022.09.648.

[41] S. Makris, F. Dietrich, K. Kellens, and S. J. Hu, “Automated assembly of non-rigid objects,” *CIRP Annals*, vol. 72, no. 2, pp. 513–539, Jan. 2023, doi: 10.1016/j.cirp.2023.05.003.

[42] M. Breznik, B. Buchmeister, and N. Vujica Herzog, “Assembly Line Optimization Using MTM Time Standard and Simulation Modeling—A Case Study,” *Applied Sciences (Switzerland)*, vol. 13, no. 10, May 2023, doi: 10.3390/app13106265.

[43] Z. Li, I. Kucukkoc, and Q. Tang, “Enhanced branch-bound-remember and iterative beam search algorithms for type II assembly line balancing problem,” *Comput Oper Res*, vol. 131, Jul. 2021, doi: 10.1016/j.cor.2021.105235.

[44] M. Carlos, P. Junior, A. S. Michels, and L. Magatão, “An exact method to incorporate ergonomic risks in Assembly Line Balancing Problems,” *Comput Ind Eng*, vol. 183, 2023, [Online]. Available: https://doi.org/10.1016/j.cie.2023.109414

[45] M. A. Abdous, X. Delorme, D. Battini, F. Sgarbossa, and S. Berger-Douce, “Assembly line balancing problem with ergonomics: a new fatigue and recovery model,” *Int J Prod Res*, vol. 61, no. 3, pp. 693–706, 2023, doi: 10.1080/00207543.2021.2015081.

[46] G. Jia, Y. Zhang, S. Shen, B. Liu, X. Hu, and C. Wu, “Load Balancing of Two-Sided Assembly Line Based on Deep Reinforcement Learning,” *Applied Sciences (Switzerland)*, vol. 13, no. 13, Jul. 2023, doi: 10.3390/app13137439.

[47] S. E. A. El Ahmadi, L. El Abbadi, and S. Elrhanimi, “EFFICIENCY IMPROVEMENT OF AUTOMOTIVE ASSEMBLY LINES USING SIMPLE ASSEMBLY LINE BALANCING PROBLEM TYPE-E,” *Logforum*, vol. 19, no. 2, pp. 183–193, 2023, doi: 10.17270/J.LOG.2023.810.

[48] M. T. Çelik and S. Arslankaya, “Solution of the assembly line balancing problem using the rank positional weight method and Kilbridge and Wester heuristics method: An application in the cable industry,” *Journal of Engineering Research (Kuwait)*, vol. 11, no. 3, pp. 182–191, Sep. 2023, doi: 10.1016/J.JER.2023.100082.

[49] E. Álvarez-Miranda, J. Pereira, and M. Vilà, “Analysis of the simple assembly line balancing problem complexity,” *Comput Oper Res*, vol. 159, Nov. 2023, doi: 10.1016/j.cor.2023.106323.

[50] E. Álvarez-Miranda, S. Chace, and J. Pereira, “Assembly line balancing with parallel workstations,” *Int J Prod Res*, vol. 59, no. 21, pp. 6486–6506, 2021, doi: 10.1080/00207543.2020.1818000.

[51] H. A. Sedding, “Mixed-model moving assembly line material placement optimization for a shorter time-dependent worker walking time,” *Journal of Scheduling*, 2023, doi: 10.1007/s10951-023-00787-5.

[52] I. O. Yilmazlar and M. E. Kurz, “Mixed-model Sequencing with Reinsertion of Failed Vehicles: A Case Study for Automobile Industry,” Jul. 2023, [Online]. Available: https://doi.org/10.48550/arXiv.2307.11869

[53] S. E. Hashemi-Petroodi, S. Thevenin, and A. Dolgui, “Mixed-Model Assembly Line Design with New Product Variants in Production Generations,” in *IFAC-PapersOnLine*, Elsevier B.V., 2022, pp. 25–30. doi: 10.1016/j.ifacol.2022.09.363.

[54] M. Eghtesadifard, M. Khalifeh, and M. Khorram, “A systematic review of research themes and hot topics in assembly line balancing through the web of science within 1990–2017,” *Comput Ind Eng*, vol. 139, Jan. 2020, doi: 10.1016/j.cie.2019.106182.

[55] M. H. Kharuddin and M. F. Ramli, “A Review on Methods to Improve and Balance the Assembly Line,” in *IOP Conference Series: Materials Science and Engineering*, Institute of Physics Publishing, Mar. 2020. doi: 10.1088/1757-899X/767/1/012022.

[56] E. Ghorbani Totkaleh, F. Sekkay, S. Keivanpour, and D. Imbeau, “Ergonomic Assembly Line Balancing Problems Evolution and Future Trends with Insights into Industry 5.0 Paradigm,” 2023.

[57] S. Mazumder, S. Padmanabhan, and M. Thenarasu, “Assembly Line Balancing And Workstation Design For A Manufacturing Industry,” *INTERNATIONAL JOURNAL OF SCIENTIFIC & TECHNOLOGY RESEARCH*, vol. 9, no. 03, pp. 6470–6475, 2020.

[58] Y. L. Jiao, H. Q. Jin, X. C. Xing, M. J. Li, and X. R. Liu, "Assembly line balance research methods, literature and development review," *Concurrent Engineering Research and Applications*, vol. 29, no. 2. SAGE Publications Ltd, pp. 183–194, Jun. 01, 2021. doi: 10.1177/1063293X20987910.

[59] V. V Pachghare and R. S. Dalu, "Assembly Line Balancing Methods-A Case Study," *International Journal of Science and Research (IJSR)*, vol. 3, no. 5, pp. 1901–1905, 2014, [Online]. Available: https://paper.researchbib.com/view/paper/19195

[60] M. Balaji, S. N. Dinesh, S. Raja, R. Subbiah, and P. Manoj Kumar, "Lead time reduction and process enhancement for a low volume product," *Mater Today Proc*, vol. 62, pp. 1722–1728, Jan. 2022, doi: 10.1016/j.matpr.2021.12.240.

[61] S. G. Gebeyehu, M. Abebe, and A. Gochel, "Production lead time improvement through lean manufacturing," *Cogent Eng*, vol. 9, no. 1, 2022, doi: 10.1080/23311916.2022.2034255.

[62] M. Rahmani, A. Romsdal, F. Sgarbossa, J. O. Strandhagen, and M. Holm, "Towards smart production planning and control; a conceptual framework linking planning environment characteristics with the need for smart production planning and control," *Annu Rev Control*, vol. 53, pp. 370–381, Jan. 2022, doi: 10.1016/j.arcontrol.2022.03.008.

[63] O. Bongomin, J. I. Mwasiagi, E. O. Nganyi, and I. Nibikora, "A complex garment assembly line balancing using simulation-based optimization," *Engineering Reports*, vol. 2, no. 11, Nov. 2020, doi: 10.1002/eng2.12258.

[64] D. Dinler and M. K. Tural, "Exact solution approaches for the workload smoothing in assembly lines," *Engineering Science and Technology, an International Journal*, vol. 24, no. 6, pp. 1318–1328, Dec. 2021, doi: 10.1016/j.jestch.2021.03.013.

[65] K. Syahputri, R. M. Sari, Anizar, I. Rizkya, J. Leviza, and I. Siregar, "Improving Assembly Line Balancing Using Moodie Young Methods on Dump Truck Production," in *IOP Conference Series: Materials Science and Engineering*, Institute of Physics Publishing, Jan. 2018. doi: 10.1088/1757-899X/288/1/012090.

[66] S. O. Ongbali, S. A. Afolalu, S. A. Oyedepo, A. K. Aworinde, and M. A. Fajobi, "A study on the factors causing bottleneck problems in the manufacturing industry using principal component analysis," *Heliyon*, vol. 7, no. 5, p. e07020, 2021, doi: 10.1016/j.heliyon.2021.e07020.

[67] W. Urban and P. Rogowska, "The Case Study of Bottlenecks Identification for Practical Implementation to the Theory of Constraints," *Multidisciplinary Aspects of Production Engineering*, vol. 1, no. 1, pp. 399–405, 2018, doi: 10.2478/mape-2018-0051.

[68] S. Hoedt, A. Claeys, E. H. Aghezzaf, and J. Cottyn, "Real time implementation of learning-forgetting models for cycle time predictions of manual assembly tasks after a break," *Sustainability (Switzerland)*, vol. 12, no. 14, Jul. 2020, doi: 10.3390/su12145543.

[69] P. T. Zacharia and A. C. Nearchou, "Balancing assembly lines operating with heterogeneous workers under uncertainty in task processing times," *Engineering Computations (Swansea, Wales)*, vol. 38, no. 10, pp. 3853–3878, 2021, doi: 10.1108/EC-09-2020-0507.

[70] J. Kádárová, J. Janeková, and A. Suhányiová, "Possibilities to Increase Assembly Line Productivity Using Different Management Approaches," *Processes*, vol. 10, no. 3, Mar. 2022, doi: 10.3390/pr10030553.

[71] S. R. Vijayakumar and P. Suresh, "Computers & Industrial Engineering Lean based cycle time reduction in manufacturing companies using black widow based deep belief neural network," *Comput Ind Eng*, vol. 173, no. August, p. 108735, 2022, doi: 10.1016/j.cie.2022.108735.

[72] P. Tshabalala and R. B. Kuriakose, "Integrating IoT Sensors to Setup a Digital Twin of a Mixed Model Stochastic System for Real-Time Monitoring," *Lecture Notes in Networks and Systems*, vol. 693, pp. 311–319, Jul. 2023, [Online]. Available: https://link.springer.com/chapter/10.1007/978-981-99-3243-6_24

[73] A. Johan and D. Soediantono, “Literature Review of the Benefits of Lean Manufacturing on Industrial Performance and Proposed Applications in the Defense Industries,” *Journal of Industrial Engineering & Management Research*, vol. 3, no. 2, pp. 2722–8878, 2022, doi: https://doi.org/10.7777/jiemar.v3i2.272.

[74] J. Bhamu and K. S. Sangwan, “Lean manufacturing: Literature review and research issues,” *International Journal of Operations and Production Management*, vol. 34, no. 7, pp. 876–940, 2014, doi: 10.1108/IJOPM-08-2012-0315.

[75] A. Palange and P. Dhatrak, “Lean manufacturing a vital tool to enhance productivity in manufacturing,” in *Materials Today: Proceedings*, Elsevier Ltd, 2021, pp. 729–736. doi: 10.1016/j.matpr.2020.12.193.

[76] C. Maware and D. M. Parsley, “The Challenges of Lean Transformation and Implementation in the Manufacturing Sector,” *Sustainability (Switzerland)*, vol. 14, no. 10, May 2022, doi: 10.3390/su14106287.

[77] N. Troncoso, H. Cancela, P. Piñeyro, F. Quezada, and O. C. Vásquez, “The product-mold-machine manufacturing problem: Complexity, MILP models and constructive heuristics,” *Comput Ind Eng*, p. 109937, Feb. 2024, doi: 10.1016/j.cie.2024.109937.

[78] N. P. Campana, M. Iori, and M. C. O. Moreira, “Mathematical models and heuristic methods for the assembly line balancing problem with hierarchical worker assignment,” *Int J Prod Res*, vol. 60, no. 7, pp. 2193–2211, 2022, doi: 10.1080/00207543.2021.1884767.

[79] S. Khlil, H. Al-Khazraji, and Z. Alabacy, “Solving Assembly Production Line Balancing Problem Using Greedy Heuristic Method,” *IOP Conf Ser Mater Sci Eng*, vol. 745, no. 1, 2020, doi: 10.1088/1757-899X/745/1/012068.

[80] A. Mumani, O. Abu-Farsakh, S. Obaidat, and A. Momani, “A GRA-based approach for optimal selection of SALBP-1 assembly line balancing heuristics,” *Journal of Engineering Research*, Nov. 2023, doi: 10.1016/j.jer.2023.11.019.

[81] V. Kumar and S. M. Yadav, "A state-of-the-Art review of heuristic and metaheuristic optimization techniques for the management of water resources," *Water Supply*, vol. 22, no. 4, pp. 3702–3728, 2022, doi: 10.2166/ws.2022.010.

[82] K. Z. Gao, Z. M. He, Y. Huang, P. Y. Duan, and P. N. Suganthan, "A survey on meta-heuristics for solving disassembly line balancing, planning and scheduling problems in remanufacturing," *Swarm Evol Comput*, vol. 57, Sep. 2020, doi: 10.1016/j.swevo.2020.100719.

[83] M. M. Razali, M. F. F. Ab. Rashid, and M. R. A. Make, "Assessment of metaheuristic algorithms to optimize of mixed-model assembly line balancing problem with resource constraints," *Journal of Modern Manufacturing Systems and Technology*, vol. 4, no. 2, pp. 73–83, 2020, doi: 10.15282/jmmst.v4i2.4787.

[84] M. Rabbani, Z. Mousavi, and H. Farrokhi-Asl, "Multi-objective metaheuristics for solving a type II robotic mixed-model assembly line balancing problem," *Journal of Industrial and Production Engineering*, vol. 33, no. 7, pp. 472–484, 2016, doi: 10.1080/21681015.2015.1126656.

[85] A. Ladj, Z. Wang, O. Meski, F. Belkadi, M. Ritou, and C. Da Cunha, "A knowledge-based Digital Shadow for machining industry in a Digital Twin perspective," *J Manuf Syst*, vol. 58, pp. 168–179, Jan. 2021, doi: 10.1016/j.jmsy.2020.07.018.

[86] D. Mourtzis and N. Balkamos, "Design of Manufacturing Systems Based on Digital Shadow and Robust Engineering," *Smart Machines and Intelligent Manufacturing*, 2023, doi: https://doi.org/10.3390/app13085184.

[87] C. Brecher, M. Dalibor, B. Rumpe, K. Schilling, and A. Wortmann, "An Ecosystem for Digital Shadows in Manufacturing," *Procedia CIRP*, vol. 104, pp. 833–838, 2021, doi: 10.1016/j.procir.2021.11.140.

[88] V. Badenko, N. Bolshakov, and F. Becker, "Integration concept of Digital Shadows and BIM for a long-term optimal decision support in factory planning," pp. 1–14, 2021, doi: http://dx.doi.org/10.21203/rs.3.rs-248614/v1.

[89] M. Behery *et al.*, "Digital Shadows for Robotic Assembly in the World Wide Lab," in *Procedia CIRP*, Elsevier B.V., 2023, pp. 165–170. doi: 10.1016/j.procir.2023.08.030.

[90] P. Tshabalala and R. B. Kuriakose, "Designing an Experimental Setup for Digital Twins in Modern Manufacturing—A Case Study Using a Water Bottling Plant," *Lecture Notes in Networks and Systems*, vol. 516, pp. 615–622, 2023, doi: 10.1007/978-981-19-5221-0_58.

[91] M. Kunath and H. Winkler, "Integrating the Digital Twin of the manufacturing system into a decision support system for improving the order management process," *Procedia CIRP*, vol. 72, no. March, pp. 225–231, 2018, doi: 10.1016/j.procir.2018.03.192.

[92] A. AboElHassan, A. H. Sakr, and S. Yacout, "General purpose digital twin framework using digital shadow and distributed system concepts," *Comput Ind Eng*, vol. 183, Sep. 2023, doi: 10.1016/j.cie.2023.109534.

[93] S. Attaran, M. Attaran, and B. G. Celik, "Digital Twins and Industrial Internet of Things: Uncovering operational intelligence in industry 4.0," *Decision Analytics Journal*, vol. 10, Mar. 2024, doi: 10.1016/j.dajour.2024.100398.

[94] Z. Huang, Y. Shen, J. Li, M. Fey, and C. Brecher, "A survey on AI-driven digital twins in industry 4.0: Smart manufacturing and advanced robotics," *Sensors*, vol. 21, no. 19. MDPI, Oct. 01, 2021. doi: 10.3390/s21196340.

[95] M. Føre *et al.*, "Digital Twins in intensive aquaculture — Challenges, opportunities and future prospects," *Computers and Electronics in Agriculture*, vol. 218. Elsevier B.V., Mar. 01, 2024. doi: 10.1016/j.compag.2024.108676.

[96] A. Billey and T. Wuest, "Energy digital twins in smart manufacturing systems: A case study," *Robot Comput Integr Manuf*, vol. 88, p. 102729, Aug. 2024, doi: 10.1016/j.rcim.2024.102729.

[97] P. Tshabalala and R. B. Kuriakose, "Analyzing the Performance of a Digital Shadow for a Mixed-Model Stochastic System," in *Lecturer Notes in Networks Systems*, vol.

461, Harish Sharma, Ed., Singapore: Springer, 2022, pp. 651–660. [Online]. Available: https://doi.org/10.1007/978-981-19-2130-8_50

[98] M. Attaran and B. G. Celik, "Digital Twin: Benefits, use cases, challenges, and opportunities," *Decision Analytics Journal*, vol. 6, Mar. 2023, doi: 10.1016/j.dajour.2023.100165.

[99] O. T. Eleftheriou and C.-N. Anagnostopoulos, "Digital twins: A brief overview of applications, challenges and enabling technologies in the last decade," *Digital Twin*, vol. 2, p. 2, 2022, doi: 10.12688/digitaltwin.17581.1.

[100] A. Mazumder *et al.*, "Towards next generation digital twin in robotics: Trends, scopes, challenges, and future," *Heliyon*, vol. 9, no. 2. Elsevier Ltd, Feb. 01, 2023. doi: 10.1016/j.heliyon.2023.e13359.

[101] M. Liebenberg and M. Jarke, "Information systems engineering with Digital Shadows: Concept and use cases in the Internet of Production," *Inf Syst*, vol. 114, 2023, doi: 10.1016/j.is.2023.102182.

[102] F. Becker *et al.*, "A Conceptual Model for Digital Shadows in Industry and Its Application," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 13011 LNCS, pp. 271–281, 2021, doi: 10.1007/978-3-030-89022-3_22.

[103] M. Sommer, J. Stjepandić, S. Stobrawa, and M. von Soden, "Automated generation of digital twin for a built environment using scan and object detection as input for production planning," *J Ind Inf Integr*, vol. 33, no. April, 2023, doi: 10.1016/j.jii.2023.100462.

[104] T. Riedelsheimer, S. Gogineni, and R. Stark, "Methodology to develop Digital Twins for energy efficient customizable IoT-Products," in *Procedia CIRP*, Elsevier B.V., 2021, pp. 258–263. doi: 10.1016/j.procir.2021.01.040.

[105] R. van Dinter, B. Tekinerdogan, and C. Catal, "Predictive maintenance using digital twins: A systematic literature review," *Information and Software Technology*, vol. 151. Elsevier B.V., Nov. 01, 2022. doi: 10.1016/j.infsof.2022.107008.

[106] M. Bandala *et al.*, "Digital twin challenges and opportunities for nuclear fuel manufacturing applications," *Nuclear Engineering and Design*, vol. 420, Apr. 2024, doi: 10.1016/j.nucengdes.2024.113013.

[107] M. R. Enders and N. Hoßbach, "Dimensions of digital twin applications - A literature review," *25th Americas Conference on Information Systems, AMCIS 2019*, no. August 2019, 2019.

[108] D. Jones, C. Snider, A. Nassehi, J. Yon, and B. Hicks, "Characterising the Digital Twin: A systematic literature review," *CIRP J Manuf Sci Technol*, vol. 29, pp. 36–52, 2020, doi: 10.1016/j.cirpj.2020.02.002.

[109] W. Kritzinger, M. Karner, G. Traar, J. Henjes, and W. Sihn, "Digital Twin in manufacturing: A categorical literature review and classification," *IFAC-PapersOnLine*, vol. 51, no. 11, pp. 1016–1022, 2018, doi: 10.1016/j.ifacol.2018.08.474.

[110] M. F. Davila R, F. Schwark, L. Dawel, and A. Pehlken, "Sustainability Digital Twin: a tool for the manufacturing industry," *Procedia CIRP*, vol. 116, pp. 143–148, 2023, doi: 10.1016/j.procir.2023.02.025.

[111] F. Longo, A. Padovano, L. Nicoletti, M. Elbasheer, and R. Diaz, "Digital twins for manufacturing and logistics systems: is simulation practice ready?," in *33rd European Modeling and Simulation Symposium, EMSS 2021*, Dime University of Genoa, 2021, pp. 435–442. doi: 10.46354/i3m.2021.emss.062.

[112] M. Singh, E. Fuenmayor, E. P. Hinchy, Y. Qiao, N. Murray, and D. Devine, "Digital twin: Origin to future," *Applied System Innovation*, vol. 4, no. 2, pp. 1–19, 2021, doi: 10.3390/asi4020036.

[113] N. J. Lemphane, B. Kotze, and R. B. Kuriakose, "A Review on Current IoT-Based Pasture Management Systems and Applications of Digital Twins in Farming," *Advances in Intelligent Systems and Computing (AISC)*, vol. 1404, pp. 173–180, 2022, doi: https://doi.org/10.1007/978-981-16-4538-9_18.

[114] Y. Wei, T. Hu, L. Dong, and S. Ma, "Digital twin-driven manufacturing equipment development," *Robot Comput Integr Manuf*, vol. 83, Oct. 2023, doi: 10.1016/j.rcim.2023.102557.

[115] M. Ebni, S. M. H. Bamakan, and Q. Qu, "Digital Twin based Smart Manufacturing; From Design to Simulation and Optimization Schema," in *Procedia Computer Science*, Elsevier B.V., 2023, pp. 1216–1225. doi: 10.1016/j.procs.2023.08.109.

[116] B. Hickey, D. C. Gachon, and D. J. Cosgrove, "Digital Twin – A Tool for Project Management in Manufacturing," *Procedia Comput Sci*, vol. 217, pp. 720–727, 2023, doi: 10.1016/j.procs.2022.12.268.

[117] Y. Lu, C. Liu, K. I. K. Wang, H. Huang, and X. Xu, "Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues," *Robotics and Computer-Integrated Manufacturing*, vol. 61. Elsevier Ltd, Feb. 01, 2020. doi: 10.1016/j.rcim.2019.101837.

[118] Q. Feng *et al.*, "Multi-level predictive maintenance of smart manufacturing systems driven by digital twin: A matheuristics approach," *J Manuf Syst*, vol. 68, pp. 443–454, Jun. 2023, doi: 10.1016/j.jmsy.2023.05.004.

[119] C. da Cunha, O. Cardin, G. Gallot, and J. Viaud, "Designing the digital twins of reconfigurable manufacturing systems: Application on a smart factory," in *IFAC-PapersOnLine*, Elsevier B.V., 2021, pp. 874–879. doi: 10.1016/j.ifacol.2021.08.103.

[120] J. B. Clarion, J. François, I. Grebennik, and R. Dupas, "A simulated annealing approach for optimizing layout design of reconfigurable manufacturing system based on the workstation properties," in *IFAC-PapersOnLine*, Elsevier B.V., 2022, pp. 1657–1662. doi: 10.1016/j.ifacol.2022.09.635.

[121] H. Aguilar, A. García-Villoria, and R. Pastor, “Heuristic and metaheuristic procedures for the buffer sizing problem in parallel assembly lines balancing problem with multi-line workstations and different cycle times,” *Comput Oper Res*, vol. 157, p. 106285, Sep. 2023, doi: 10.1016/j.cor.2023.106285.

[122] G. Lugaresi, P. L. B. Dos Santos, A. C. Lona, M. Rossi, A. Matta, and E. Zancul, “A Digital Twin for Production Control Based on Remaining Cycle Time Prediction,” in *2023 Winter Simulation Conference (WSC)*, IEEE, Dec. 2023, pp. 3284–3295. doi: 10.1109/WSC60868.2023.10407531.

[123] 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,” *Journal of Discrete Mathematical Sciences and Cryptography*, vol. 23, no. 2, pp. 329–336, 2020, doi: 10.1080/09720529.2020.1741184.

[124] Q. Qi, Z. Xu, and P. Rani, “Big data analytics challenges to implementing the intelligent Industrial Internet of Things (IIoT) systems in sustainable manufacturing operations,” *Technol Forecast Soc Change*, vol. 190, May 2023, doi: 10.1016/j.techfore.2023.122401.

[125] L. De De Nardis, G. Caso, and M. G. Di Benedetto, “ThingsLocate: A ThingSpeak-Based Indoor Positioning Platform for Academic Research on Location-Aware Internet of Things,” *Technologies (Basel)*, vol. 7, no. 3, p. 50, 2019, doi: 10.3390/technologies7030050.

[126] Z. Li, I. Kucukkoc, and J. M. Nilakantan, “Comprehensive review and evaluation of heuristics and meta-heuristics for two-sided assembly line balancing problem,” *Comput Oper Res*, vol. 84, pp. 146–161, 2017, doi: 10.1016/j.cor.2017.03.002.

[127] M. Eghtesadifard, M. Khalifeh, and M. Khorram, “A systematic review of research themes and hot topics in assembly line balancing through the web of science within 1990–2017,” *Comput Ind Eng*, vol. 139, no. November 2019, p. 106182, 2020, doi: 10.1016/j.cie.2019.106182.