A Novel Approach for Production Planning and Productivity Improvements in Dynamic Production Systems using DES and Heuristic Methods

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Ruba Al-zqebah

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School of Mechanical and Mechatronic Engineering
Faculty of Engineering and Information Technology
University of Technology Sydney
NSW - 2007, Australia

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CERTIFICATE OF ORIGINAL AUTHORSHIP

I, Ruba Al-zqebah declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Mechanical and Mechatronic Engineering/ Faculty of Engineering and IT at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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Abstract

The contemporary manufacturing landscape, characterized by global competition and the advent of Industry 4.0, necessitates a paradigm shift in production systems. Small and medium enterprises (SMEs) face the daunting task of surviving in this highly competitive environment marked by short product lifecycles. Even larger enterprises grapple with the challenges posed by increased connectivity and complexity resulting from Industry 4.0 tools. This complexity is further magnified in diverse production settings, such as the High-Mix Low-Volume (HMLV) and Low-Mix High-Volume (LMHV) environments, each presenting unique scheduling and variability challenges. This thesis addresses the pressing need for an advanced production planning approach capable of accommodating uncertainty and capturing the intricacies of different industrial settings. It identifies a knowledge gap in existing research, highlighting a lack of integrated approaches that combine heuristic optimization algorithms and discrete event simulation (DES) comprehensively. While heuristic algorithms often overlook real-world stochastic and dynamic elements, existing stochastic methods, such as stochastic programming and fuzzy programming, exhibit limitations in accuracy and manageability. The research focuses on developing a holistic framework that seamlessly integrates heuristic optimization algorithms and DES, providing decision-makers with a more realistic and comprehensive perspective on the challenges associated with production systems. The proposed approach aims to address multiple production challenges in stochastic and dynamic systems, offering adaptability across diverse industries and operations, whether manual or automated. Ultimately, the goal is to enhance overall productivity and streamline the planning processes in the ever-evolving landscape of modern manufacturing. This thesis was conducted based on three studies that capture different industrial settings: 1. Woolshed industry as an example of a heavily manual process, 2. Additive manufacturing as an example of (HMLV), 3. Assembly line balancing as an example of (LMHV). Research findings show the effectiveness of the proposed approach in diverse production settings. In the woolshed industry, challenges related to facility layout and resource planning are successfully addressed. In additive manufacturing, the integration of discrete event simulation and genetic algorithms reduces total production time, with notable advantages as the factory scales up. The study on assembly line balancing demonstrates a 15% improvement in throughput and resource utilization compared to heuristic methods in isolation in the low mix high volume industry.

DEDICATION

To my parents . . .

To my husband . . .

To my daughters . . .

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To my relatives and friends.

Table of Contents

List of Figures

List of Tables

CHAPTER 1

INTRODUCTION

1.1 Motivation

Manufacturing is becoming increasingly competitive due to global competition. The latest industrial revolution, known as Industry 4.0, led to the advancement of manufacturing systems. This is facilitated through big data availability, advanced automation, the Internet of Things (IoT), additive manufacturing (AM), digital twins, machine learning, and simulation [8]. This advancement accelerates innovation, production, and market adaptability, leading to shorter product life cycles. Surviving in such a highly competitive environment with short product life cycles poses a significant challenge for small and medium enterprises (SMEs) [9]. Strategic planning and efficient resource management are essential to support these enterprises. This is not limited to SMEs; even in large enterprises, the system becomes more connected and complex, raising the need for a production planning tool to capture this complexity and variability. Therefore, a dynamic approach is essential to address the complexity and various production settings. For instance, the High-Mix Low-Volume (HMLV) production environment is marked by high variability and complexity attributed to a broad range of task processing times, resulting in scheduling challenges and potential errors [10]. This underscores the necessity for an advanced scheduling approach to accommodate uncertain conditions. On the other hand, the Low-Mix High-Volume (LMHV) production environment, in contrast to HMLV, exhibits lower product variability, often associated with mass production [11]. However, despite this, the evolution of technology and intensified competition among enterprises introduce challenges related to demand fluctuations. This dynamic presents complexities and hurdles for the assembly line, impacting workload distribution, resource efficiency, and the overall production planning process. This thesis aims to develop a production planning approach that captures the variability and uncertainty conditions in various industrial settings to solve several production challenges and improve overall productivity.

1.2 Identifying Knowledge Gap

Extensive research has been conducted on the planning, designing, and performance evaluation of various production systems. Including heuristics, a strategic method used to solve specific types of problems, and discrete event simulation (DES), a method of studying a system by simulating it digitally. For instance, Sahu and Pradhan [12] conducted a review of existing methods aimed at enhancing production system productivity. This research showed a predominant focus on either heuristic optimization algorithms such as [13], and [14] or DES as seen in works like [15], and [16]. Heuristic algorithms treated the examined problems in a static or deterministic manner, overlooking the real-world elements of stochasticity and dynamism [17]. While stochastic methods, such as stochastic programming [18], fuzzy programming [19], and stochastic dynamic programming [20] attempt to capture real system stochasticity, but they tend to have lower accuracy compared to DES and are challenging to apply to pure and complex mathematical models [21]. Therefore, DES appeals as a promising approach to these stochastic and complex conditions. Nevertheless, there is a conspicuous gap in the investigation of integrated approaches that combine heuristic methods and DES for diverse problems and settings. Only a limited amount of research has developed a framework to guide decision-makers in the production planning process (see chapter 2 for a detailed overview). This thesis seeks to build a framework that takes into account the dynamic nature of the system and its rooted noisy conditions, offering a more realistic and comprehensive perspective on the challenges associated with production systems.

1.3 Research Focus

This thesis centers on the development of a holistic approach designed to address multiple production challenges simultaneously, thereby improving productivity and the production planning process in stochastic and dynamic systems. The objective is to construct an approach that is adaptable for use across diverse industries, encompassing both small and large-scale operations, whether manual or automated. The aim is to enhance overall productivity and streamline the planning processes of these industries.

1.4 Scope and Research Questions

The objective of this study is to examine the main research question, which is: ***How can the implementation of advanced hybrid techniques that combine DES and heuristics enhance productivity and production planning across diverse industrial settings within a dynamic production system?*** To fulfill the objective, the following three research questions have been formulated:

- RQ1: To what extent can discrete event simulation be used in evaluating the productivity of heavily manual production enterprises?

- RQ2: What is the effectiveness of combining DES with a metaheuristic method (Genetic algorithm) to enhance productivity in High-Mix Low-Volume (HMLV) Manufacturing?

- RQ3: What is the effectiveness of combining DES with heuristic methods to solve the assembly line balancing problem (ALBP) in Low -Mix High-Volume (LMHV) Manufacturing?

1.5 Research Approach

There are several ways to study and boost the productivity in manufacturing systems. To illustrate, Figure 1.1 presents the approaches used to examine any system [1]. Conducting experiments with actual systems to observe their behavior under new conditions is feasible but typically uncommon and costly [22]. Therefore, utilizing a model for experimentation is preferred. These models can either be physical or mathematical. Physical models provide a tangible representation of the studied object, often scaled either up or down [22]. On the other hand, mathematical models express the real-life system through equations and constraints [23]. Analytical solutions involve the use of formulas to obtain optimal results, but this approach demands significant computing time and is unsuitable for intricate and stochastic systems. On the contrary, heuristics offer nearly optimal solutions within a reasonable computation time frame, making them well-suited

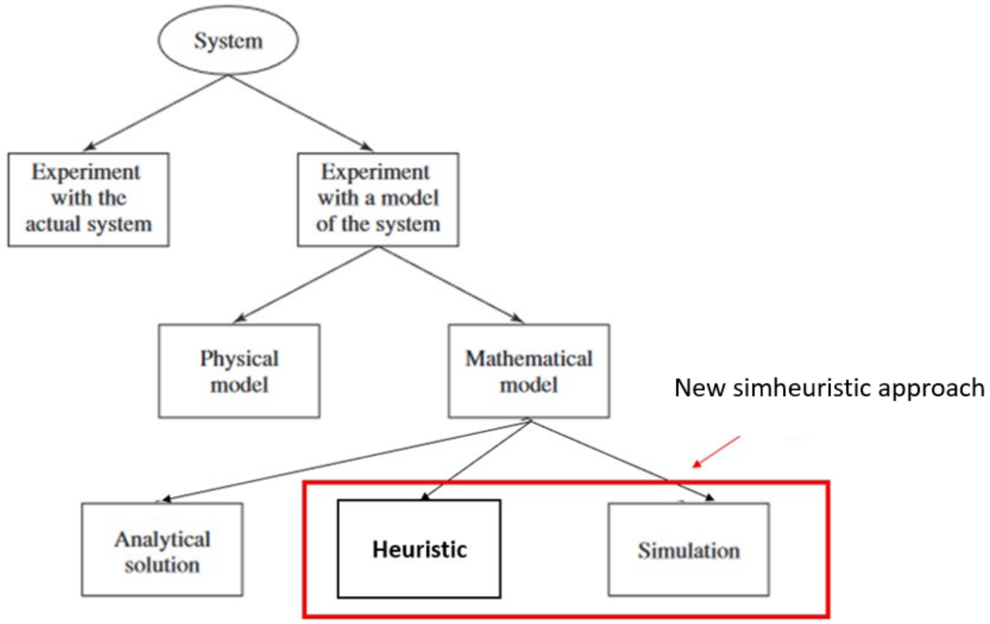

Figure 1.1: Approaches for studying a system [1]

for complex systems. However, their effectiveness may be limited to specific problem characteristics, and they may not be well-equipped to account for the stochastic elements inherent in the system. Meanwhile, simulation is one of the industry 4.0 tools, which involves a virtual representation of the real-life system to mimic its performance. DES is a method widely utilized in manufacturing for testing system changes digitally before the changes are physically implemented [7]. This tool is excellent for portraying stochastic and dynamic systems. However, it is not designed to discover optimal solutions. In operation research, the combination of DES and heuristic optimization was treated separately until the advancement of computational power was raised in the last two decades, which facilitated their combination. However, developing a well-designed interaction is critical and depends on the type of problem. This thesis aims to address the gap in existing studies by exploring the combination of DES and heuristics in the field of production planning. This combination, known as simheuristic, is a type of optimization algorithm that integrates simulation or any of its forms into heuristic or metaheuristic techniques [17].

To adopt a comprehensive approach, three distinct areas encompassing diverse industrial settings have been chosen for investigation. Each of these industrial settings serves as an individual case study. Data about the current state of production parameters, such as processing time, failure rate, number of resources, and layout, will be collected through on-site field visits. The selection of these industries and the rationale behind their choice are outlined as follows:

- **Wool industry:** This industry relies heavily on manual processes. Moving toward automation or changing the facility design has faced some resistance to introducing wool growers due to a lack of awareness and the absence of simulation studies conducted in this field. This thesis highlighted the importance of DES in such an environment and its role in developing a robust production plan before implementing it.

- **Additive manufacturing industry:** Production planning in this field is still in the early stage, while much research in additive manufacturing focuses on part quality and printing technology [24], there is a gap in factory-level management and production planning using simulation. This gap can be attributed to the technology's predominant application in prototype construction and its relatively recent introduction to high-production settings, which has left this issue largely unexplored in the existing literature. Determining the optimal number of resources is important due to the high costs associated with tools, high variability, and processing time between jobs. This is particularly relevant as the industry transitions from the prototype phase to the production phase. Finally, it serves as an example of the HMLV industry.

- **Assembly line balancing:** Uneven workload between workstations due to short life cycle time and changes in demands. This creates an environment conducive to studying, especially in situations with significant variability. The existing approach in this field relies on heuristic techniques or employs simulation to assess the effectiveness of these heuristics. This work covers the gap by integrating heuristic task allocation methods with DES to capture various factory settings. This field is a good example of the LMHV industry.

To address the research questions (RQs), each paper focused on a specific research question related to different industrial areas (Figure 1.2).

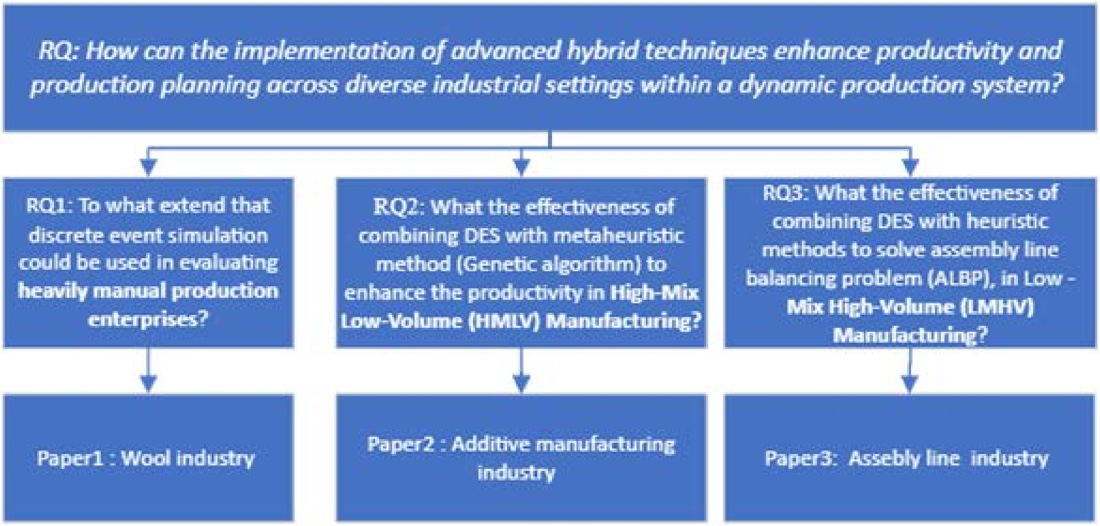

Figure 1.2: Research questions and the papers that answer them

1.6 Structure of this Thesis

The structure of this thesis is as follows: chapter 2 provides a literature review and background on simulation, heuristics, and their integration into production systems. This section encompasses various topics, including the role of simulation in manufacturing, the different types of simulation, a comprehensive definition of discrete event simulation (DES), its applications, and an exploration of its advantages and disadvantages. It also includes an Overview of heuristic and metaheuristic algorithms, their types, advantages, and disadvantages, and introduces literature on the integration of simulation and optimization in manufacturing. Additional literature relevant to the respective case studies will be presented in their respective chapters. Chapters 3, 4, and 5 each introduce a paper that addresses one of the sub-research questions. Paper 1: Woolshed Throughput Improvement Using Discrete Event Simulation, Paper 2: Powder Bed Fusion Factory Productivity Increase Using Discrete Event Simulation and Genetic Algorithm, Paper 3: A Novel Approach and Case Study to Assembly Line Balancing using Discrete Event Simulation and Heuristic Methods. Cross-case analysis and discussion are presented in chapter 6. Finally, chapter 7 concludes the research and its academic contribution, practical implications, limitations, and future work.

Chapter 2

Literature review

2.1 Overview of simulation and discrete event simulation

In this section, the use of simulation in manufacturing in general and its uses in several areas to solve specific manufacturing challenges have been introduced in section 2.1.1. The types of simulations used in manufacturing are presented in section 2.1.2. Section 2.1.3 defines the discrete event simulation (DES) and its components. Section 2.1.4 presents the DES application. Lastly, the advantages and disadvantages of DES are presented in section 2.1.5.

2.1.1 Simulation in manufacturing

Manufacturing is a type of production system that involves converting materials and information into goods to meet human needs[25]. In today's highly competitive business landscape, the manufacturing industry faces ongoing challenges in creating innovative products within a short period of time. To thrive in the market, companies must promptly respond to customer demands, necessitating robust planning, design, scheduling, machining, and assembly capabilities [26]. Simulation plays a vital role in responding to these challenges. As shown in Velazco [2], a significant body of research is conducted about utilizing simulation in evaluating the resources required (workers, machines, equipment), timing for each resource on a specific task, evaluating material handling systems,

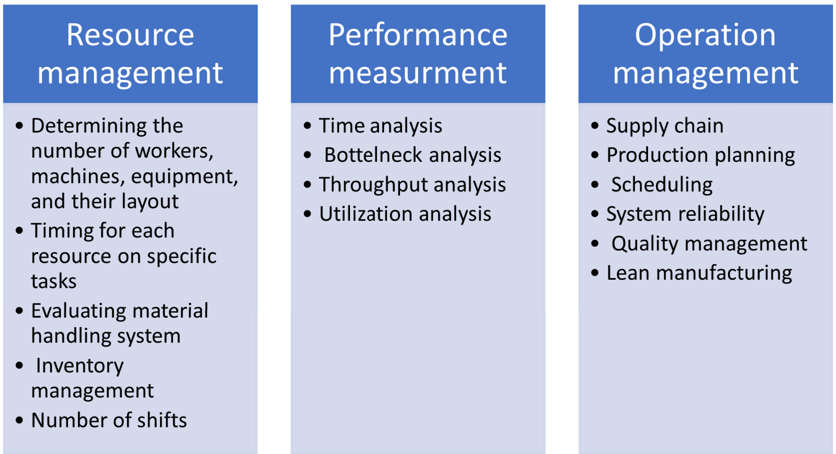

Figure 2.1: Manufacturing challenges across three key fields that have been addressed by simulation. Recreated from [2]

and inventory management. Moreover, simulation proves it is effective in measuring systems performance, such as measuring throughput and identifying bottlenecks; it has been used to measure the time that the parts spend on the system, such as work in progress (WIP) time, inventory time, processing time, etc. Another primary application of simulation in operation management includes managing the supply chain, production planning, scheduling, system reliability, quality management, and lean manufacturing. In summary, simulation has effectively tackled several specific manufacturing challenges, which can be categorized into three broad groups (Figure 2.1).

2.1.2 Types of simulation

Simulation can be defined as the use of a computer model to mimic a real or planned system. This model can then be used to predict the performance of that system in several alternative situations. However, simulation is a broad concept that encompasses various types of simulation. According to Jahangirian [5], the most widely used simulation techniques for production planning in manufacturing include the following: discrete event simulation, system dynamics, and Agent-based modeling. This section aims to introduce each of these techniques and highlight their differences.

Discrete event simulation(DES): It is a stochastic modeling technique employed to simulate real-world systems, which can be broken down into distinct processes that independently progress through time. Events occur within specific processes and are associated with logical timestamps. The outcomes of these events can be passed on to other processes, potentially leading to the generation of new events scheduled for future timestamps [27].

System dynamics(SD): In this terminology, a system is made up of components that interact to generate an object, and dynamic pertains to changes happening over time [28]. SD is a widely used simulation technique for modeling continuous processes characterized by nonlinear behavior and extensive feedback within the system [29]. In practical terms, SD is frequently applied in strategic policy analysis [28].

Agent-based modeling (ABM): This type of simulation investigates how people, things, places, and time interact with each other. It examines the outcomes resulting from the actions of individuals within the system as well as the impacts on individuals due to the actions of the system [30].

Comparison between these simulation types:

SD is deterministic in nature, while DES is stochastic. DES focuses on the meso details of a system, while SD adopts a macroscopic perspective, considering the overall behavior only [31]. Both DES and ABM are stochastic, but DES focuses more on the process flow based on networks of queues, where entities wait in queues for processing, whereas ABM systems do not involve the concept of queues and focus on the individual entities in the system and their interactions. Figure 2.2 demonstrates that these three classifications tackle various levels of abstraction and specifics, making them applicable across different decision-making stages, namely macro level, meso level, and micro level. Demonstrating that DES is the most fitting approach for operational and manufacturing levels since it focuses on process and workflow. The following sections will offer a more comprehensive exploration of DES and elucidate the rationale for its selection.

2.1.3 Discrete event simulation

Discrete-event simulation (DES) is an approach used to represent a system by capturing a series of events that transpire at distinct time intervals. These events symbolize alterations in the system's state, encompassing instances like customer arrivals or departures, machine breakdowns or repairs, and task commencements or completions. Through the simulation of these events, one can observe the system's behavior as it evolves over time and assess performance metrics such as throughput, utilization, cost, and waiting time. To construct a discrete-event simulation model, there are four fundamental components that must be defined [32]: entities, resources, queues, and logic. Entities represent the various objects that traverse the system, such as customers, products, or orders. Resources encompass the elements that offer services or possess capacity for the entities,

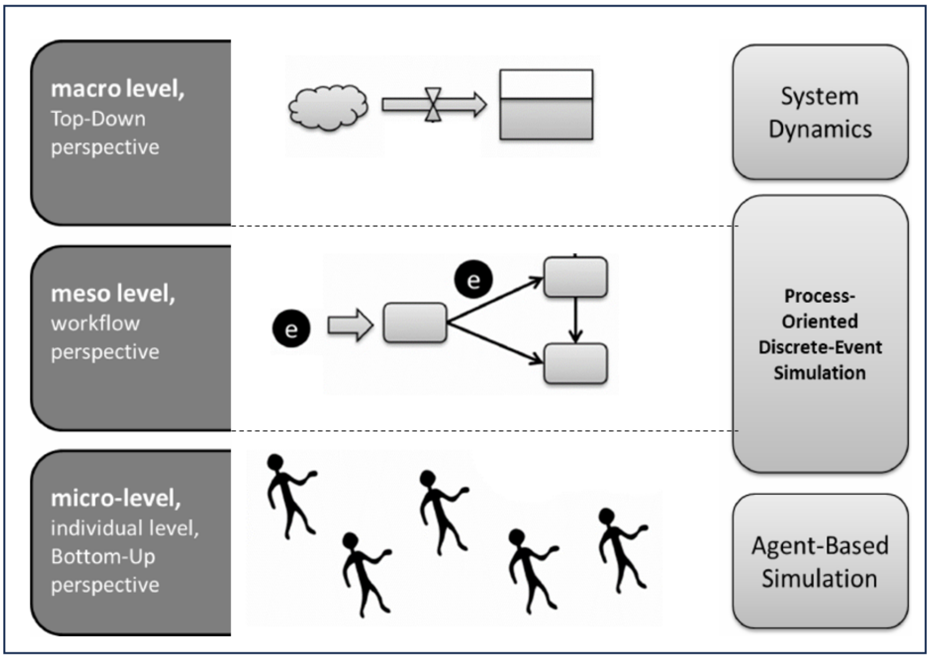

Figure 2.2: Types of simulation and their levels of abstraction [3]

such as machines, workers, or vehicles. Queues denote the locations where entities wait for resources, such as lines, buffers, or storage areas. Logic comprises the set of rules that dictate the behavior of the system, including the arrival and departure of entities, the request and release of resources, and the decisions or actions undertaken by the entities.

2.1.4 Application of DES

In recent decades, discrete event simulation has gained significant traction across diverse application areas. This growing trend can be attributed to both the increased adoption of technology across various scientific fields and the innovative utilization of dedicated software programs by skilled experts with high computing power. According to Jahangirian [5], the main application of DES within manufacturing is listed in Table 2.1.

Table 2.1 illustrates the comprehensive applications of (DES) in manufacturing, showcasing its ability to analyze various aspects such as assembly line balancing (ALB), capacity planning, transportation management, inventory management, process engineering, production planning, scheduling, and supply chain management to enhance efficiency and productivity at different operational levels.

Table 2.1: Application of DES in manufacturing [5]

#	Application	Description
1	Assembly line balancing	Distribute the task among workstations on an assembly line in the equivalent way
2	Capacity planning	Uncertainty arise from fluctuations in capacity levels, the need to expand existing resources, and the desire to enhance current operations to boost capacity
3	Transportation management	Optimizing routes and improving overall efficiency in transportation operations.
4	Inventory management	Cost of holding, buffer capacity, economic order quantity, determining batch sizes, Just-in-time
5	Process engineering	Designing for new technologies, scheduling rules, facility layout, bottlenecks identification, performance measurements
6	Production planning	Optimizing resource allocation, identifying bottlenecks, determining batch sizes, layout scheduling rules
7	Scheduling	Throughput, delivery on time, job sequencing, minimize idle time and lead time
8	Supply chain management	Inventory and distribution systems

2.1.5 Advantages and disadvantages of DES

DES offers the ability to analyze localized system changes and examine their impact on the overall system without disrupting ongoing operations, provides pre-implementation system behavior visualization, and captures real-world complexity. It can effectively incorporate randomness, variability, dependencies, feedback loops, and interactions within systems' components. On the other hand, it has some limitations, such as it requires specialized training, falls short of fully representing the real-world environment, and can be time-consuming without optimization capabilities. Table 2.2 summarizes DES's advantages and disadvantages.

Table 2.2: Advantages (from [6]) and disadvantages (from [7]) of DES

Advantages	Disadvantages
Analyze how localized changes affect the overall system.	Need Training to build a simulation model.
Analyze the system without interrupting existing operations.	Not fully presented of the real-world environment.
Visualize the effect of changes on the system before implementing it	Cost and time consuming of building a digital model.
Capture complexity, uncertainty, randomness, and variability.	Not an optimization tool.

One of the disadvantages of DES is that it remains extensively utilized for designing and analyzing manufacturing systems. It can be contended that DES finds even broader applications in manufacturing systems than in any other field. Several factors contribute to this phenomenon, including the following [33]:

- The advancement in automation raised the need for DES because automated systems are more complex, and they can only be analyzed by simulation.
- High cost of equipment, which raises the need for extensive planning before investing in unnecessary equipment.
- Significant decrease in computing costs due to faster and more affordable PCs.
- The advancements in simulation software, particularly the introduction of graphical user interfaces (GUIs), have resulted in a reduction in model development time. The presence of animation in simulations enhanced comprehension and increased utilization of simulation among manufacturing managers.

After clarifying the first main pillar of the proposed approach (DES), how it works, and its effectiveness in solving various problems in the manufacturing field, the subsequent sections will spotlight the second pillar, optimization methods (heuristic and metaheuristics). This will involve furnishing definitions for each method, providing a broad overview of their mechanisms, showcasing popular examples, and their advantages and disadvantages.

2.2 Overview of heuristic and metaheuristic method

Heuristic and metaheuristic are both optimization techniques for solving problems, but they differ in their scope and application **A heuristic** is a problem-dependent method that uses knowledge about the problem to find a solution[34]. **A metaheuristic** is a problem-independent method that groups several guidelines to find a solution for a wide range of problems. A metaheuristic does not require specific knowledge about the problem [35].

2.2.1 Types of heuristics methods

There are three primary categories of heuristics [36]:

- **Trial-and-error:** This heuristic involves employing various strategies until a successful one is found. Individuals randomly select potential actions and continue exploring different options until they settle on a choice they believe will lead to the most optimal decision.

- **Rule-based:** This type of heuristics entails applying general principles or rules while solving problems. This form of heuristic thinking is widely considered as the prevalent approach in problem-solving today.

- **Adaptive learning:** Adaptive learning heuristics incorporate past experiences into the decision-making process for future choices. Feedback from previous experiments is utilized to guide and inform subsequent ones.

Heuristic algorithms are typically designed for a particular problem. For instance, in the domain of facility layout problems, a variety of rule-based heuristics have been developed to tackle such challenges. These include constructive methods like ALDEP (Automated Layout Design Program) [37], and CORELAP (Computerized Relationship Planning) [38], as well as improvement heuristics like CRAFT (Computerized Relative Allocation of Facilities Technique) [39]. Similarly, in the context of assembly line balancing problems (ALBP), heuristic approaches such as ranked positional weight technique (RPW) [40], KWC (Kilbridge and Wester's method) [41], and others are employed to optimize task allocation and sequencing. In this study, the choice of heuristics is based on the specific characteristics of the problem and their broad applicability.

2.2.2 Types of metaheuristics

Meta-heuristic algorithms consist of four main groups: Evolution-inspired, Nature-inspired, Human-inspired, and Natural-like inspired [42].

1. Evolution-inspired: the algorithms that use mathematical models to simulate biological evolution. They begin by creating a random population, with each individual representing a potential solution. Through natural selection and genetic variation, new offspring are generated. An alternative strategy is then used to decide which individuals will continue as offspring and parents. Genetic algorithm (GA) is one of the most well-known algorithms in this category. Which is a technique used to solve optimization problems, both constrained and unconstrained. It operates by simulating the process of natural selection, similar to biological evolution. The algorithm iteratively modifies a population of individual solutions, selecting random individuals as parents to generate the offspring for the next generation. As generations progress, the population evolves, moving closer to an optimal solution[43].

2. Nature-inspired: the algorithms that are based on the inspiration of behavior of natural phenomena, including aspects like animal behaviors and various chemical and physical systems [44]. Famous examples include the Artificial Bee Colony (ABC) optimization algorithm, which mimics how bees search for food and communicate information about food sources in terms of distance, time, location, and quantity [45]. Another example is Particle Swarm Optimization [46] and Ant Colony Optimization (ACO) [47].

3. Human-inspired: This algorithm is inspired by human social behavior and their response to the environment [42]. Some examples are Teaching Learning Based Optimization (TLBO) [48] and social-based Algorithms (SBA) [49].

4. Natural-like inspired: This type is inspired by phenomena or nonlinear sciences, including physics, chemistry, and mathematical laws. A well-known example is simulated annealing (SA) [50], which is an optimization technique inspired by the metal cooling process to find the global optimal solution for the objective function. The annealing process is the process of heating the metals and then letting them cool slowly to enhance their mechanical properties [51].

In this research, GA was chosen as the optimization method based on previous research that highlighted the robust performance of GA in the context of Discrete Event

Simulation [52]. Additionally, GA is well suited to problems with a large set of possible parameters and where an obvious global maximum or minimum is not readily apparent, such as in scheduling scenarios with fluctuating resource availability [53].

2.2.3 Advantages and disadvantages of heuristics and metaheuristics

There are several advantages and disadvantages of using heuristics and metaheuristics. Heuristics, for example, offer distinct advantages in solving complex problems that could take long computation time or be impossible to solve using exact methods. So, it could be used for quick decision-making, reducing computation efforts, and capturing uncertainty. However, their lack of precision and inflexible nature, marked by rigidity and resistance to change, can impede adaptation to evolving circumstances. Despite their data independence, heuristics pose a risk of biased decision-making.

On the other hand, similar to heuristics, metaheuristics reduce the time required for solving optimization problems that are hard to solve using exact methods. They are, however, more flexible than heuristics, and their flexibility allows application to a wide range of problems, irrespective of the problem type. Yet, the generic design of metaheuristic algorithms may limit their ability to exploit specific problem knowledge, potentially resulting in suboptimal solutions. While enabling extensive exploration for finding global optima, these algorithms often exhibit a long convergence time, requiring numerous iterations for an acceptable solution. Additionally, the presence of multiple parameters in metaheuristics necessitates careful tuning for optimal performance, posing a challenge in finding suitable values and highlighting the sensitivity of the algorithm's effectiveness to parameter settings. The advantages and disadvantages of heuristic and metaheuristic are summarized in Table 2.3.

In summary, both heuristic and metaheuristic methods strive to achieve efficient solutions within a short time frame compared to traditional numerical approaches, specifically, the exact approaches, which often entail lengthy computation times, especially for NP-hard problems, and in some complex problems, it becomes impossible. Therefore, heuristics and metaheuristics are the most suitable for use. Even if these methods cannot guarantee finding the optimal solution, they can provide a good enough solution depending on the nature of the problem and search cost. In this thesis, heuristic and metaheuristic were utilized in the proposed approach to solve several NP-hard problems such as scheduling and assigning tasks to workstations in ALBP.

Table 2.3: Advantages and disadvantages of heuristic and metaheuristics

Optimization method	Advantages	Disadvantages
Heuristics	Quick decision making which reduce efforts [54].	Lack of precision (optimal solutions are not guaranteed) [55].
	Effective decision-making under uncertainty [54].	Inflexible nature, heuristics often exhibit rigidity and resistance to change, impeding the ability to adapt to new information or evolving circumstances [56].
	Data independence means heuristics are not dependent on the quantity of available data [54].	Risk of biased decision-making [57].
Metaheuristics	Addressing the limitations of traditional numerical approaches decrease the time required for solving optimization problems [58].	Meta-heuristic algorithms are typically designed to be generic and do not take advantage of specific problem knowledge. Consequently, their ability to exploit the structure or characteristics of a problem may be limited, potentially leading to suboptimal solutions [59].
	Flexible and applicable to a wide range of problems, regardless of the problem's type [58].	Meta-heuristic algorithms may exhibit a long convergence time as they often require numerous iterations to reach an acceptable solution [60].
	Enables extensive exploration for finding global optima [58].	Meta-heuristic algorithms often include multiple parameters that require careful tuning for optimal performance. Finding suitable parameter values can be a challenging task, and the algorithm's effectiveness can be influenced by the sensitivity of its performance to parameter settings [61].

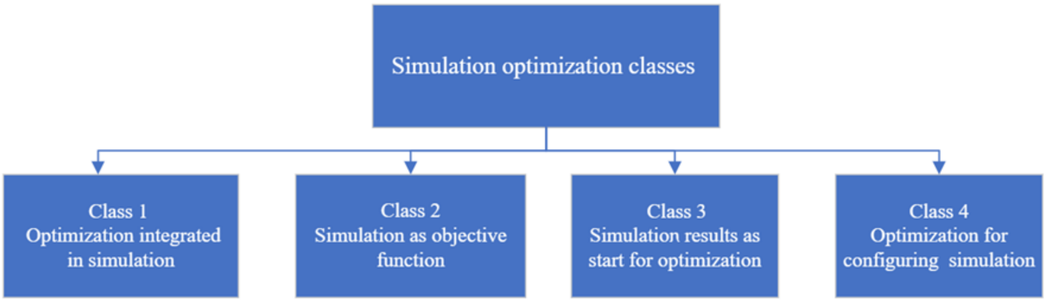

Figure 2.3: Simulation optimization classes

2.3 Integration of simulation and optimization in manufacturing

This chapter provides an overview of existing literature concerning the integration of simulation and optimization in manufacturing. It outlines the nature of integration and highlights distinctions from the proposed new simheuristic approach in a general context. However, a more in-depth exploration of relevant literature regarding the wool industry, additive manufacturing, and assembly line balancing is presented in subsequent sections, with detailed discussions tailored to the specific studies covered in the chapters of the papers (Chapter 3, Chapter 4, and Chapter 5).

In the field of operations research, simulation and optimization have traditionally been regarded as separate approaches until two decades ago when a significant advancement in computational power led to the start of combining them together [62]. However, crafting a well-designed interaction is crucial depending on the type of problem. According to Rabe [63], the integration of simulation with optimization techniques can be categorized into four distinct classes: optimization integrated into simulation, simulation as the objective function, simulation results as a start for optimization, and optimization for configuring simulation (Figure 2.3).

1. Optimization integrated into simulation: In this class, the simulation temporarily stops and employs optimization to assess a particular problem. The outcome of this optimization is then fed back to the simulation, allowing it to resume its activity.

2. Simulation as an objective function: Optimization offers a potential solution that undergoes evaluation using simulation. The simulation-derived results are sub-

sequently integrated back into the optimization process to generate alternative solutions.

3. Simulation results as a start for optimization: The simulation is carried out before the optimization process. The simulation provides the initial parameters or starting point for the optimization.

4. Optimization for configuring simulation: In this case, the simulation is utilized to assess the feasibility of a solution identified by the optimization process.

The challenges that this combination seeks to solve are [64]:

1. Uncertainty: This is tackled through various conventional approaches, including stochastic programming, fuzzy programming, and stochastic dynamic programming. However, these methods exhibit significantly lower accuracy and detail compared to simulation approaches. In addition to the difficulty when handling pure mathematical models.

2. The complexity of the problem and the nonlinear relationships make it hard to be modeled mathematically.

In the assembly line balancing context, there are several studies that combined DES and optimization, such as Unal et al. [65]. They proposed a heuristic algorithm for line balancing and used simulation to evaluate the performance of the heuristic under various line configurations (class 4). Eryuruk et al. [66] used two heuristic methods called Probabilistic Line Balancing Technique and Largest Set Rule Algorithm to balance multi-model assembly line, then they used simulation as a supported tool to compute time losses and queues (class2). Mirzaei et al. [67] used the Grouping Evolution Strategy (GES) algorithm to minimize the number of workstations and smoothness index and maximize the line efficiency for two configurations: straight and U-shaped assembly lines. Then, DES will capture the stochastic behavior of the production line for both layouts (class 4). Lee et al. [68] used simulation as an evaluation tool for the output of a genetic algorithm to enhance productivity, line efficiency, and tardiness (class 4). Yu and Su [69] integrated simulation to the genetic algorithm for solving mixed model assembly line problems. Their approach focuses on integrating task assignments using GA and sequencing decisions using simulation; their goal is to minimize cycle time (class 2). In contrast, this research is geared towards minimizing the number of workstations and

maximizing resource utilization while keeping the cycle time fixed.
Overall, all studies in assembly line balancing used simulation as an evaluating tool under the class “Simulation as objective function” or used the simulation as an alternative solution to capture the stochastic nature of the system.
Juan et al. [70] used the second class to minimize the makespan based on the stochastic processing time of the flow shop scheduling problem. Guimarans et al. [71] introduced a simulation and heuristic algorithm for the two-dimensional vehicle routing problem with stochastic travel times. Bernaus et al. [72] used this approach to solve the facility location problem and compared the performance of this approach against the traditional stochastic programming method; they observed that this approach effectively addresses large-scale instances that are beyond the capabilities of the stochastic programming method within reasonable computational time. Finally, Rabe et al. [73] used the case of “Simulation results as a start for optimization” to solve the logistic problem. Dengiz and Alabas [74] introduced a tabu search algorithm combined with a simulation model of a just-in-time system to determine the optimal number of kanbans that align with production demands. Tiacci [75] devised a hybrid approach comprising a genetic algorithm and simulation to concurrently address two manufacturing problems: the buffer allocation problem (BAP) and the assembly line balancing problem (ALBP) for a complex assembly line. This comprehensive solution accounts for stochastic task times, parallel workstations, and buffers between workstations.
The integration of DES and optimization has been utilized in various applications such as scheduling [70] and routing problems [76], facility location problems [77], logistics networks [73], buffer allocation problem, and assembly line balancing problem [75], and various other contexts. However, most of the existing research focused on either class 2 (Simulation as an objective function) or class 4 (optimization for configuring simulation), and all of the conducted research targeted problems with one known setting (specific number of resources). However, the new approach aims to utilize simulation alongside optimization by combining class 2 and class 3 to test various settings, considering the facility scaling up, such as changing the number of machines and workers. Additionally, it involves grouping various problems together, such as facility layout problems, resource planning, scheduling, assembly line balancing, and bottleneck identification to enhance productivity.

This integration leads to solving a third challenge, which is modeling alternative scenarios. Diverging from conventional methods and prior composite classes that evaluate various input parameters and their effects on performance indicators, the new approach goes beyond just diverse inputs. It also considers varying process structures. For example, it could examine the impact of adding extra counters in a restaurant on the queue length and delivery time, while other approaches collect and model the problem depending on the specific number of resources without considering other what-if scenarios.

The upcoming sections address three areas of study. Each area answers one of the research questions. Chapter 3 introduces research Paper 1 under the title " Woolshed Throughput Improvement Using Discrete Event Simulation". This paper aims to show the effectiveness of discrete event simulation in evaluating woolshed designs to address the highly manual production environment. In chapter 4, the second study, which was presented in paper 2 under the title "Powder Bed Fusion Factory Productivity Increase Using Discrete Event Simulation and Genetic Algorithm" was used to answer the second research question about the effectiveness of integrating DES and genetic algorithm in evaluating low mix high volume production environment. Chapter 5 presented the third paper titled "A Novel Approach and Case Study to Assembly Line Balancing using Discrete Event Simulation and Heuristic Methods" spotted the light on the third research question about the effectiveness of integrating DES and heuristic methods in evaluating low mix high volume environment. A discussion of the three studies and their finding on the main research question is presented in chapter 6. Finally, chapter 7 wrapped up the research's conclusion.

CHAPTER 3

Paper 1: Woolshed Throughput Improvement Using Discrete Event Simulation

This section introduces the first study which aims to answer the first research question "To what extent that discrete event simulation could be used in evaluating productivity of heavily manual production enterprises?" The wool industry is used as an example of this type of production since it is a small enterprise that totally relies on manual processes and this approach has not been tested before in this area. A case study was conducted in one of the Australian woolsheds and utilized DES to evaluate the facility design including the layout and other improvement scenarios to boost it is productivity. The paper thoroughly details the research methodology and presents the findings in depth.

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Woolshed Throughput Improvement Using Discrete Event Simulation

Ruba Al-zqebah[1], Florian Hoffmann[2], Nick Bennett[1], Jochen Deuse[1], Lee Clemon[1]

[1]*Centre for Advanced Manufacturing, University of Technology Sydney (Australia)*
[2]*Institute of Production Systems, TU Dortmund (Germany)*

ruba.Al-zqebah@student.uts.edu.au, florian.hoffmann@ips.tu-dortmund.de, Nicholas.Bennett@uts.edu.au, Jochen.Deuse@uts.edu.au, lee.clemon@uts.edu.au

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Abstract:

Purpose: Computer-aided production engineering simulation is a common approach in the search for improvements to real systems. They are used in various industrial sectors and are a basis for process improvement. Such production simulations have found limited use in the wool industry. This study aims to compare the performance of different woolshed layouts (curved vs linear).

Design/methodology/approach: A discrete event simulation is constructed for both considered layouts in Siemens Tecnomatix Plant Simulation software. Data from an in-field observational visit to a working woolshed and industry gray literature is used to validate the simulation model. The two layouts are compared in their base configuration and with equipment and worker changes to evaluate the impacts on throughput.

Findings: In the base configurations, the curved layout reduces total worker travel time which increases production by 11 fleeces per day over the linear layout. The addition of an extra skirting table in the curved layout further increases throughout by 30 fleeces per day. The addition of more wool handlers does not have as large of an impact indicating that processing limits occur due to equipment capacity and shearer speed.

Research limitations/implications: The sample size of the collected field data was small; some data have been collected from literature and not directly measured. Processing time is assumed to be distributed uniformly as a conservative distribution form. The study's purpose is to evaluate relative differences in two different layouts using consistent worker parameters.

Practical implications: This verifies the proposed curved shed layout improves production and gives farmers the ability to compute the long-term economic impact. The results also highlight that other processing stages in the shed need adjustment for more system gains.

Originality/value: As the first application of discrete event simulation to evaluate woolsheds operations this work shows throughput gains are possible with layout, equipment, and worker changes to current practices. Additionally, this work shows the effectiveness of discrete event simulation evaluating woolshed designs. The results can be used to reduce costly experiments.

Keywords: discrete event simulation, digital model, plant simulation, woolshed

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1. Introduction

Computer-Aided Production Engineering (CAPE) is a science of representing a system or process for the intent of evaluation and examination (Barton, Joines & Morrice, 2017). This digitalization process is popular in manufacturing due to its ability to visualize and provide a better understanding of the whole manufacturing process. It is commonly used when planning a new facility or optimizing an existing one to save time, money, and effort by testing proposed ideas and options before implementing them. CAPE has been successful in enabling production evaluation and optimization in several industrial sectors (Florescu & Barabas, 2020). However, it has yet to be widely applied in on-farm agricultural processes due to skillset and access barriers (Gittins, McElwee & Tipi, 2020). In particular, it has not been used in wool handling and shearing sheds. This material flow process can benefit from the well-developed production simulation tools offered in modern CAPE software. In particular, competing shed layouts are evaluated to identify bottlenecks and offer suggestions for system improvement.

Discrete Event Simulation (DES) is a major method in CAPE. DES simulates the behavior of entities when an event happens at a specific point in time. These events are then evaluated over time. It is commonly used to simulate the performance of an actual process, system, or facility (Klingstam & Gullander, 1999). DES has been utilized by several industries such as aircraft manufacturing (Powell, 1999), healthcare (Jacobson, Hall & Swisher, 2006), supply chain management (Kogler & Rauch, 2018), material handling (Bhosekar, Ekşioğlu, Işık & Allen, 2021), and product development (Pérez-Escobedo, Azzaro-Pantel & Pibouleau, 2011) to improve production flow and reduce all forms of waste. This diverse set of applications shows the value of DES as a tool for production and logistics planning. Different approaches to categorizing the areas of application can be found in the literature. Jahangirian, Eldabi, Naseer, Stergioulas and Young (2010) examined 250 studies in simulation, which are assigned to the categories of order planning, inventory management and factory planning, among others. Negahban and Smith (2014) categorize around 290 simulation studies as production system design and planning. These categories can be assigned to the areas of planning and control of production systems (Meyr, Wagner & Rohde, 2015). Semini, Fauske and Strandhagen (2006) note that the focus is on the use of simulation in the semiconductor and automotive industries, however, the literature contains diverse application examples across several industries. Some examples use-cases include:

1. Kampa and Gołda (2018) employed DES to create three models which evaluated changes to a manufacturing system of steel casting foundry. They simulated the replacement of a human workforce with automation and evaluated the work efficacy. The results of the simulation model confirmed the benefits of replacing the manual-operated line with the automated one in terms of throughput, products quality, and production speed.
2. Siderska (2016) used plant simulation to test a model to eliminate wasted time and increase productivity in a bar stool production company.
3. Kliment, Popovič and Janek (2014) used Plant Simulation to analyze production line capacity and explain the effects of individual workstation failures on the efficiency of the whole production line. Also, an experiment was done to determine the lowest number of pallets needed to ensure the maximum use of production lines. The results showed that the elimination of 5% of bottlenecks led to an increase in production by around 5%.
4. Another application specifically for Tecnomatix Plant Simulation software was conducted by Borojevic, Jovisevic and Jokanovic (2009) to introduce a model for crankshaft production and assembly of saw engines. This model helped by identifying bottlenecks, inefficient workstations, and increasing the whole processing time by introducing buffers between workstations to reduce the transportation times. It also recommended extra machines be added to optimize the whole production process.

Thus, simulation studies have been applied in many industrial sectors for various fields of application and in combination with optimization methods for the identification of optimal process parameters. To date, the authors are aware of no such application of DES in the wool industry using DES for production enhancement.

Shearing shed research for the wool industry has focused on human factors and ergonomic design or wool quality metrics. Such ergonomics research seeks to reduce the risk of worker injury due to poor posture and repetitive actions during their work. For example, to reduce lower back pain (LBP) injuries, Harvey, Erdos, Bolam, Cox, Kennedy & Gregory (2002) analyzed different types of shed floor and floor slope to reduce the force required to drag sheep onto the shearing board. Similarly, the effect of using a back harness to support shearers has been studied by Gregory, Laughton, Carman, Milosavljevic and Callaghan (2009), while Milosavljevic, Gregory, Pal, Carman, Milburn & Callaghan (2011) investigated the amount and duration of axially twisted postures on the probability of being affected by LBP. The research concentrated on the factors that contribute toward improving wool quality and quantity, studied the influence of using chemical lice treatments (Niven & Pritchard, 1985), sheep nutrition (Kelly, Macleod, Hynd & Greeff, 1996), and shearing time (Story & Ross, 1960). None of this prior work looks at the flow of material throughout the entire shed.

Shearing shed design not only affects human and animal safety but also plays an important role in the amount and quality of harvested wool. Woolshed designs vary by shearing stand arrangement, board position, and size depending on the number of workers, skirting tables, wool presses, and location of wools bins. Traditionally, wool sheds would conform to a *linear* layout where shearing stands are arranged in a single straight line (Figure 1a). However, recent research from Australian Wool Innovation (n.d.) has proposed an alternative layout, which will be called *curved* (Figure 1b). This research uses DES to simulate the two current competing shearing shed arrangements and compare their performance. These two shed layouts are chosen as the dominate designs in industry.

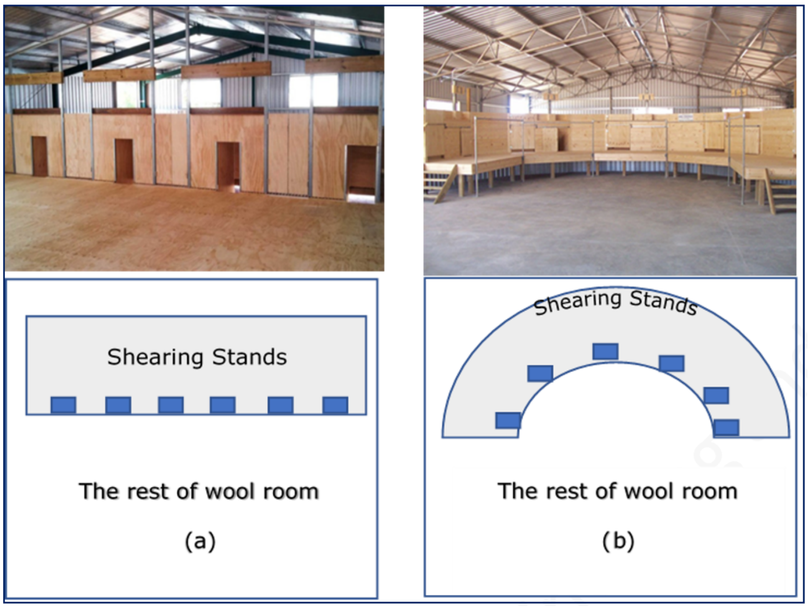

Figure 1. Shearing stands arrangement, (a) Linear layout (Shearing Shed Solutions, n.d.), (b) curved layout (Kendrick Sheds, n.d.)

2. Methodology

This section describes the steps to build and compare the digital models for both shed layouts. The digital model was defined in a systematic procedure with experimental validation (Figure 2). The objective was defined as identifying the bottlenecks in a manual on-farm wool shed, followed by collecting field data to construct the model then verify and validate the simulation. Once the model was validated, it was used to analyse the bottlenecks and the efficiency opportunities in two proposed shed layouts.

The problem is defined as evaluating which shed layout has the better performance in terms of productivity and resource utilization. Resource utilization was selected as the evaluation criteria.

Data collection is the third step and it is critical in determining the accuracy of the model. Data was collected through direct measurements of an on-farm visit during a typical shearing and wool handling day and supplemented with a review of industry reports and relevant literature.

The following subsections are organized as: an overview of the wool harvesting process in section 2.1, while section 2.2 illustrates wool processing data collection. Modelling of the shearing shed using DES in section 2.3. model verification and validation are presented in section 2.4.

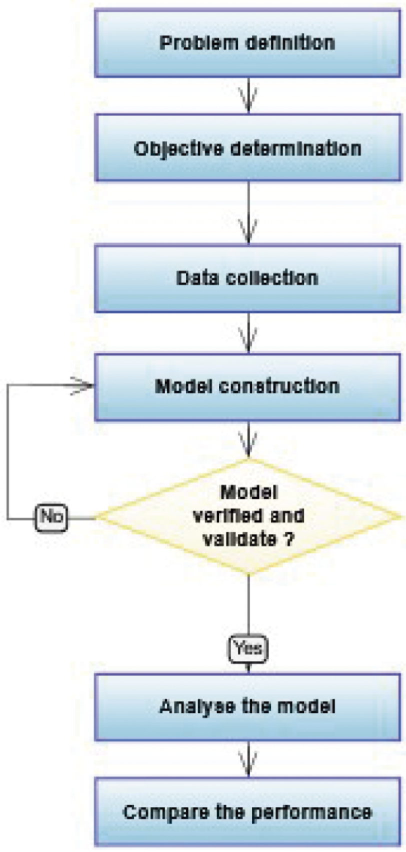

Figure 2. The procedure for building a digital production model (Ruiz-Zúñiga, Urenda-Moris & Syberfeldt, 2016; Ng, Persson & Urenda-Moris, 2008)

2.1. Overview of the Wool Harvesting Process

In general, wool harvesting comprises four main processes (Figure 3): (1) shearing; (2) skirting; (3) classing, and (4) pressing and baling:

1. Sheep are taken from catching bins by workers called *shearers* to the shearing stands. Then the shearers shear them to remove the fleece and small wool cuts.
2. The workers called *wool handlers* gather and collect fleece from shearing stands then pass it to the skirting table. Meanwhile, cleaners sweep the floor and collect short cuts of wool and send it to small bins stationed near the skirting table. At the skirting table, wool handlers carry out skirting, i.e., removing reject wool (soiled, stained, or contaminated) from the rest of the fleece.
3. The worker called a *wool classer* evaluates the fleece and categorizes it into one of multiple classes. Typically, the most valuable or largest volume class is pressed first. Wool that cannot be put in the press immediately is passed to different buffer cages according to its quality (length, strength, color, etc.) based on its designated class.

4. Finally, fleeces are added and pressed in a wool press until the bale reaches the required weight (110-204 kg). A worker called a *wool presser* fastens and seals the bale, then it is taken for labelling and moved into storage.

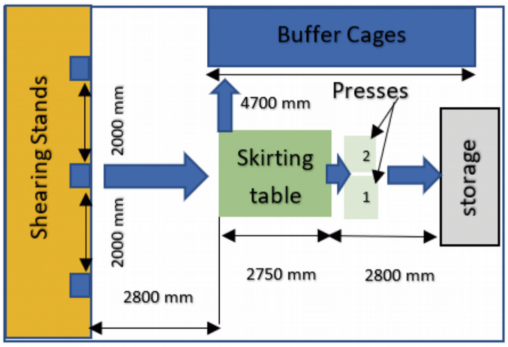

Figure 3. Shed layout overview diagram for the visited shed indicating the four main process areas: shearing stands, skirting tables and presses, buffer cages and final product storage. Workers transport the wool between stages, blue arrows represent fleece movements.

2.2. Wool Processing Data Collection

Field data and industry reported values were combined for the simulation. An actively working woolshed in Bathurst, New South Wales, Australia, was observed and data collected on in-shed wool processing for educational purposes. This data was then used for this project a later stage. The field visit was carried out to this 3-stand shearing shed on 13 August 2020. Figure 4 shows photos of this shed during the shearing and wool skirting processes, respectively. This shed is used as a source of information in constructing the digital model. Observations of the shed were made for 1 shearing session, approximately 2 hours, and recorded in a notebook. The durations of the steps/processes were measured by stopwatch and recorded. Interviews with shed staff were also conducted to ensure the data was representative. The shed contained 9 workers (3 shearers, 2 wool handlers, 1 classer, 1 presser, and 2 floating shed hands), although one staff member more than is typical, it provided useful data on processing speed for each stage and to confirm literature ranges are suitable.

In addition, training materials and literature reported values for shearing, skirting, baling, and pressing times were acquired that were complementary to the shed visit, e.g., conventional shed layout information was collected from the Australian Wool Innovation (n.d.). Measured field data was consistent with industry training materials and published processing times for both individual processes and overall shed throughputs. No tendency toward any particular probability distribution was found in the data.

Figure 4. Shearing stage (left) and skirting stage (right)

2.3. Modelling of the Shearing Shed Using Discrete Event Simulation

To visualize the current production process and compare the performance of the two sheds layouts, a digital model has been developed using a product lifecycle management (PLM) software called Tecnomatix Plant Simulation.

This software was chosen for its ability to provide effective analytical tools such as layout optimization, bottleneck analysis, diagrams for tracking material flow, and statistical data outputs (Siderska, 2016).

The constructed layout was built according to a typical shed's dimensions, collected from its design sheet (Australian Wool Innovation, n.d.). Here the distance between shearers is around 2.3m and the distance between the skirting table and shearing stands is around 6.5m in the curved layout, while the equivalent linear layout is built by adjusting the shearing stands with keeping the distances between shearers fixed.

The comparative study compares two shed designs containing 14 workers (6 shearers, 2 wool handlers, 2 cleaners (or shed hands), and 3 people doing the skirting, with one of them carrying out wool classification and 1 presser). Skirting table, shearing stand sizes and locations were taken from the current common linear layout and the more recently proposed curved layout and modeled (Figure 5). Bins, press, cage (buffer), and store locations and dimensions are arranged according to the observed layout in Bathurst facility.

Figure 5a represents the constructed model built using the PLM software to mimic the real shearing shed. The developed model consists of six shearing stands (arranged in a curve), a skirting table located in the center, surrounded by two bins on each side, two wool presses followed the skirting table, five cages, and stores. While Figure 5b represents the same shed but with the shearing stands arranged in a single straight line, this will be referred to as a *linear* layout.

Worker parameters are assumed constant for both layouts, meaning processing time, recovery time, process variation, skill level, and travel speed are kept constant in both arrangements. The perturbed variable for simulation is the location of shearing stands. Table 1 shows the parameters that were used for workers as input in both layouts. Traveling speed is 1.5 m/s and worker efficiency is 100%.

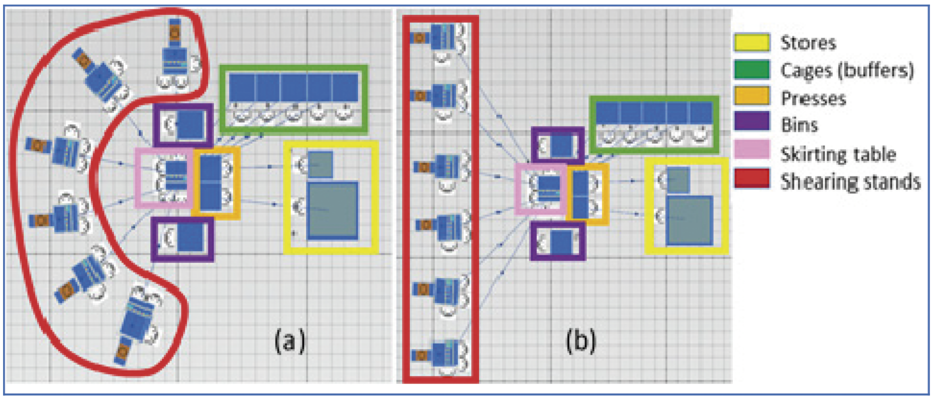

Figure 5. Shed layout in Plant Simulation, (a) Curved, (b) Linear shearing stand arrangement, blue arrows represent fleece movements

	Worker	Amount	Shift	Speed	Efficiency	Additional services	
1	*.Resources.handler	2	Day	1.5	100	handling	swiping
2	*.Resources.shearer	6	Day	1.5	100	shearing	
3	*.Resources.skirtter	3	Day	1.5	100	skirting	
4	*.UserObjects.cleaner	2	Day	1.5	100	cleaning	
5	*UserObjects classifier	1	Day	1.5	100	classifing	pressing

Table 1. Workers' parameters for both layouts in Plant Simulation

The processing and recovery time for the workers measured during the shed visit varied from 2 to 3 ½ minutes depending on the shearer's ability, as well as the sheep's size, temperament, and condition (see Appendix A for the individual measurements). In the model the processing time for the shearers follows a uniform distribution, the minimum and maximum values are varied between the six shearers, while the recovery time is set to one of two values 10 and 15 seconds. The observed processing time for skirting took between 25 to 28 seconds. For baling, processing time follows a uniform distribution between 2 minutes to 2:30 minutes, while the recovery time was 30 seconds (the mode). Based on these observations, Table 2 shows the data which is used in the model.

After collecting data, two digital models were constructed using Tecnomatix plant simulation, one for each layout as seen in Figure 6.

Process	processing time (min: sec)	Recovery time (min: sec)
Shearing 1	2:30-3:00	0:10
Shearing 2	2:40-3:00	0:10
Shearing 3	2:20-3:00	0:15
Shearing 4	2:30-2:50	0:15
Shearing 5	2:30-3:30	0:15
Shearing 6	2:30-3:00	0:15
Skirting	0:25-0:28	00:00
Balling	2:00-2:30	0:30

Table2. Processing and recovery time for shearing and skirting processes based on the collected data

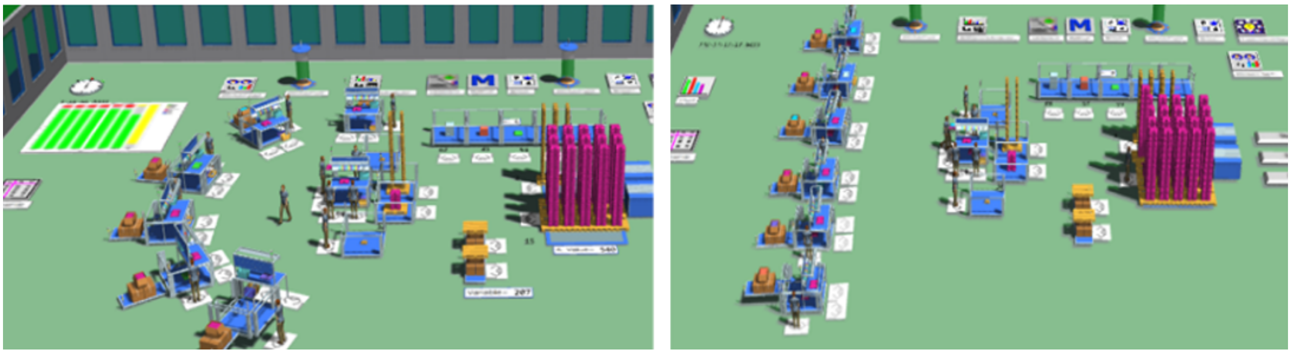

Figure 6. Tecnomatix 3D model for both layouts: curved (left), linear (right)

2.4. Model Verification and Validation

After constructing the digital model, a verification and validation process was applied to make sure that the developed digital models represent the physical model (real-life harvesting process) accurately. Verification is the process of checking that the model is working as programmed and there is no error or bugs occurred in the software. And to check the model in detail at steps during simulation to ensure every resource (worker) is correctly performing their assigned task.

The next step is validation which is the step of comparing the digital model results with the real-life results. To do the validation the amount of produced fleece from the digital model is compared with the real amount obtained from the visited shed in a model that reflects the number of workers and setup in the observed shed. The workers processed 485 fleeces in average. The digital model predicts an average of 478 per day, which results in an acceptable error of 1.4% given the expected variation.

After ensuring the performance and accuracy of the constructed models in the verification and validation stage. The base model was extended to compare the performance between the two target layouts as well as to detect production inefficiencies, such as the bottlenecks. To reduce these production inefficiencies, what-if scenarios were applied in the simulation models. The analysis results and suggested improvements are presented in the next section.

3. Results and Discussion

The model simulates a single workday of 7 hours 40 minutes of working time. According to the processing time for the six workstations within 7:40 hours, the output of the production line was 826 fleeces in the curved layout and 815 fleeces in the linear layout. Statistical analyses of work at each workstation executed at the end of the production process showed that this difference is a consequence of an increase in the shearers being blocked by the skirting table, as indicated by the increased yellow portions in Figure 7b, compared to Figure 7a.

Figure 7 also shows that the working percentage for the skirting table was 79.06% and 78.04% for the curved and linear layouts, respectively. As well as there was some blockage in the skirting process in both layouts 4.11% (curve), and 4.22% (linear), the reason behind this is the baling process. Which stops the flow of skirted fleece from buffering inside of the press. This occurs after the bale is has reached the weight limit and while it is being unloaded and a new wool pack (bag) is inserted.

A deeper look at the statistical results showed that the output of the curved layout is improved due to the wool handlers traveling shorter distances overall throughout the working day. Table 3 illustrates the total travelled distance by cleaners and wool handlers in each layout. The workers experience approx. 30% drop in distances travelled with the curved shed layout, meaning they are more often ready to receive fleeces from the shearer and deliver them to the wool table without delays. In a real shed, this has an added benefit of reducing worker effort by limiting their walking distance, which supports the human factors intention of the *curved* design.

Despite the curved layout reducing blocking, both layouts still suffer from a bottleneck created by the skirting table. Figure 7 shows the blocking percentages and blocking time for each layout.

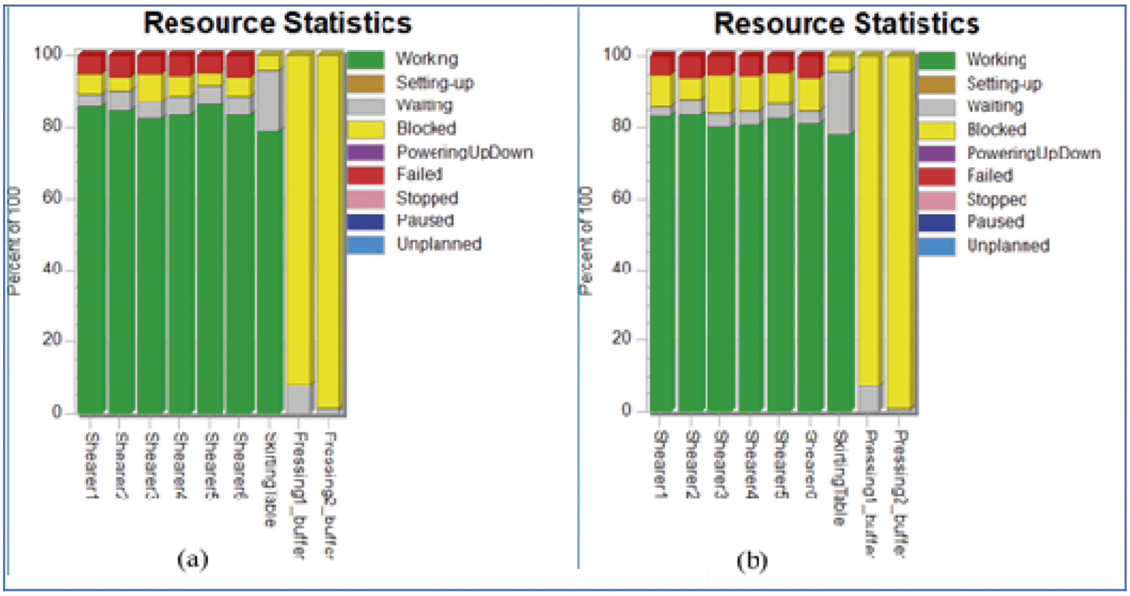

Figure 7. Resource statistics from Plant Simulation model for (a) Curved shed layout, (b) Linear shed layout

Layout / Worker	Linear (m)	Curve (m)
Cleaner1	6018	4275
Cleaner2	10081	7127
Wool handler 1	8191	5865
Wool handler 2	8841	5893

Table 3. Travelled distances by workers in each layout

The suggested solutions to increase productivity are a) adding another skirting table, b) adding extra wool handlers, or c) reducing the skirting table processing time. These scenarios have also been analyzed on the curve layout.

First solution suggestion: add another skirting table (Figure 8a). The simulation model for this solution showed satisfying effects, as it raised the production to 856 fleeces of wool within 7:40 hours. The blocking percentage and blocking time in the curved layout after this addition decreased. This makes the shearers work near full capacity, as shown in Figure 8b. However, some blockage at the shearing stations can be noticed after adding an extra skirting table and the reason behind this is the variability of wool handlers' arrival rate and the service rate variability at the skirting table. In general, adding a buffer between the skirting table and the shearer stations could be a solution to manage variability issues, but wool handling requires specific handling methods that make this infeasible. Fleeces must be passed to the skirting table directly and without mixing with other fleeces. So, carrying the fleece again from the buffer and to the skirting table would consume more time due to the extra handling and may reduce quality by spreading contaminants.

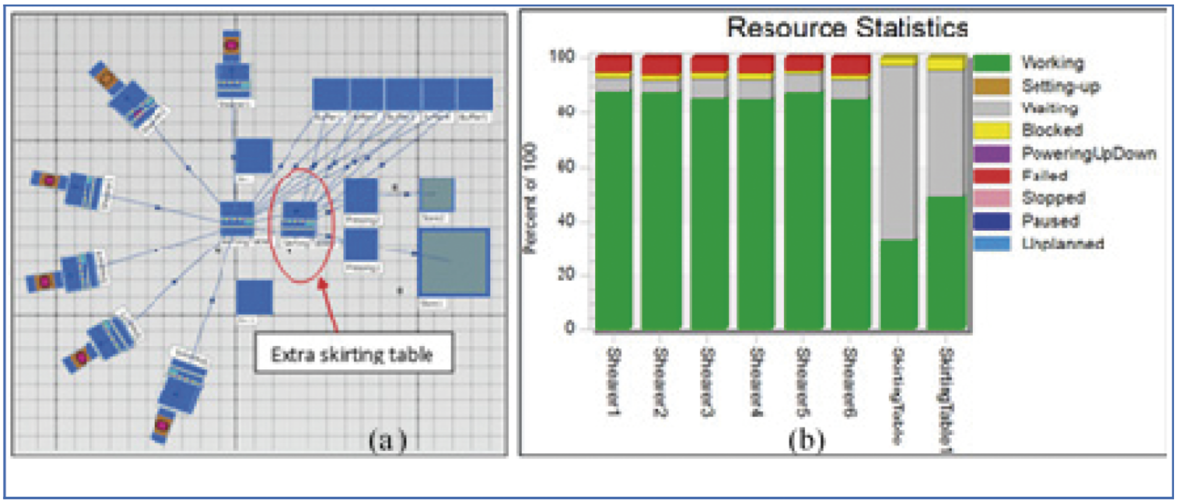

Figure 8. Plant Simulation model showing the curved wool shed layout with two skirting tables and accompanying resource statistics

The next simulated solution: add extra wool handlers. To evaluate This solution five experiments were applied. The number of wool handlers was increased from 2 to 6 workers. A proportional relationship was observed between the number of wool handlers and the output up to a saturation point. The maximum number of produced fleeces in this case when the system has 6 wool handlers was 833 as shown in Table 4. The first solution of adding a skirting table showed better results, and the additional worker(s) add more cost than the small increase in fleece is worth.

Number of wool handlers	Number of fleece (curve)
2	826
3	827
4	828
5	833
6	833

Table 4. the second scenario adding extra wool handlers

The last scenario is reducing the processing time of the skirting table by adding a worker to do the skirting or by automating the process. By utilizing DES, a set of thirty-one (31) experiments were simulated for a range of skirting processing times (10-40 sec). The results shown in Figure 9 illustrate the optimal processing time that provides the maximum operation time and maintains the highest throughput was 22 seconds which yields an output of 868 fleeces per day. This processing time ensures the shearers are not blocked as shown in Figure 10, maximising utilization.

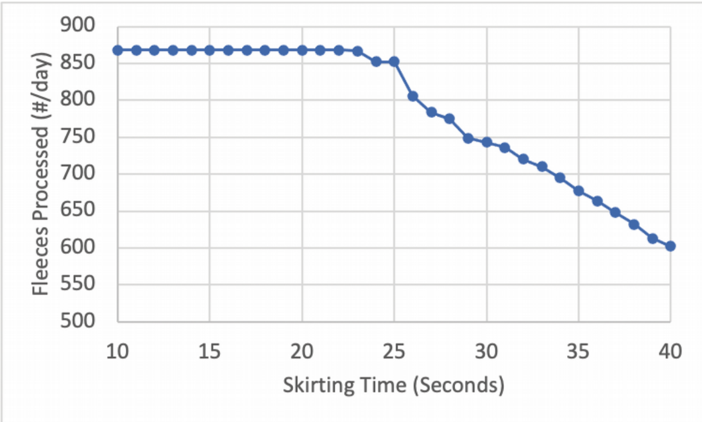

Figure 9. Number of shorn fleeces according to skirting table processing time with the optimal speed highlighted in blue

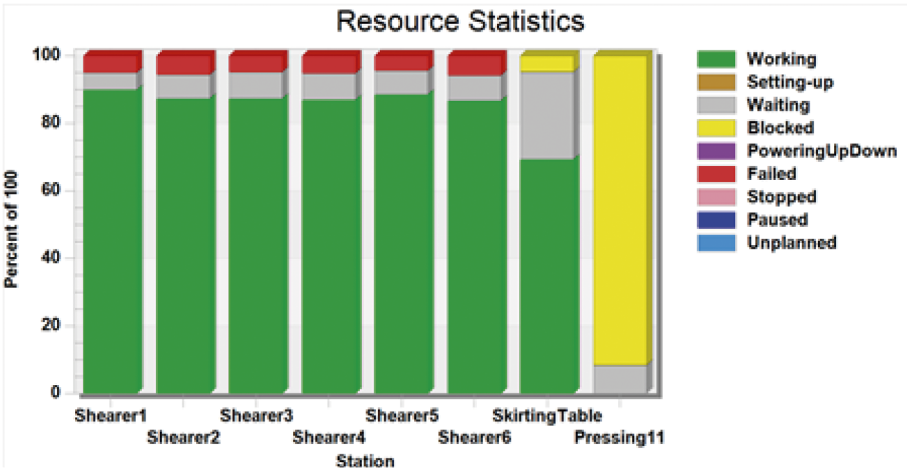

Figure 10. Resource statistics for skirting process time equal to 22 seconds

DES provides a straightforward and low-cost route to generate and evaluate potential solutions for the bottleneck. The associated layout changes show an increase in employee productivity and thus an increase in the output of the production system. Processing times are assumed to be uniformly distributed. This choice reflects the small sample size of the experiment not demonstrating a clear distributional form and provides convergence to a normal distribution should a sufficiently large simulation be performed. This property makes for a conservative estimate on the process variability with the limited data.

4. Conclusion

This study used discrete event simulation to compare the performance of different wool shed layouts (curved vs linear) and evaluate solutions to improve shearing shed performance. This is the first study of this problem for wool handling to improve production. The digital model revealed that the curved layout showed better performance than the linear layout. Specifically, the curved layout showed better performance than the linear layout by an increase in output of 11 fleeces over a one-day working period (equivalent to 33 min saving). The underpinning reason was the reduction in travelling time for workers in the curved layout, which helped to reduce the blocking at the skirting table. Several scenarios were explored to improve the production in the curve layout. Adding a second skirting table decreased the blocking problem. That meant the shearers could work near their full capacity, leading to an improvement in the throughput, this enhanced production from 826 to 856 fleeces. A second scenario of increasing the number of wool handlers' number showed that only a small gain was possible with the highest throughput of 833 with an extra four handlers. Finally, the best possible scenario was reducing the processing time for the skirting table to 22 seconds resulting in higher productivity reaches to 867 fleeces.

The paper shows how improvements in this industry can be identified and evaluated using DES. Through further simulation-based investigation of the wool harvesting process, an optimized production layout could be designed and examined with regard to its potential for improvement. This approach eliminates the need for costly planning, which is usually associated with high investment costs.

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Declaration of Conflicting Interests

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Appendix A

Field data for three shearers and skirting through using stop watch and supplementary data extracted from industry literature

Shearer	Shearing speed 1	Shearing speed 2	Shearing speed 3	Shearing speed 4	Recovery time
Shearer 1	2:30-3:00 (RSPCA Australia, n.d.)				10
Shearer 2	2:40	2:43	2:54	3:00	0:10,0:12,0:10,0:09
Shearer 3	2:20	2:27	2:48	3:00	0:12, 0:15, 0:15, 0:14
Shearer 4	2:30	2:35	2:42	2:50	0:15, 0:15, 0:15, 0:14
Shearer5	2:30-3:30 (Australian Wool Innovation, 2015a)				15
Shearer6	2:30-3:00 (RSPCA Australia, n.d.)				15
Skirting	0:25, 0:25, 0:28, 0:26				0:00
Balling	2:00-2:30 (Australian Wool Innovation, 2015b)				0:30 (Australian Wool Innovation, 2015b)

This paper addresses the first research question: " To what extent can discrete event simulation be used to evaluate the productivity of heavily manual production enterprises?"

The digital model demonstrates an average daily production of 478 fleece, with a standard deviation of 1.5. This production rate was influenced by workers' skills and other factors. Although the model assumed 100% worker utilization, this assumption did not affect the overall results or conclusions of the study because the worker utilization would work as a scaling factor and evenly scale up/down all results. So, that will not affect any ratios/ranking between the analyzed options. Additionally, the analysis explored various factors, such as testing different layouts, adding extra resources, and examining the impact of variations in human skills on production. This showcases the model's flexibility in predicting output under various conditions and provides a proof of concept, highlighting the applicability of the proposed approach to this industrial environment. Appendix A (Page 83) presents the SimTalk programming codes used to control the production flow in the woolshed case study. It also includes the results from running the model five times, demonstrating how changes in the number of wool handlers affected the number of sheared fleeces within the curve layout scenario. The next chapter explores the second area of study, which covers high-mix, low-volume industrial environments.

CHAPTER 4

Paper 2: Powder Bed Fusion Factory Productivity Increase Using Discrete Event Simulation and Genetic Algorithm

This paper addresses the second research question "*What is the effectiveness of combining DES with metaheuristic method (Genetic algorithm) to enhance productivity in High-Mix Low-Volume (HMLV) Manufacturing?* " Answering this question could demonstrate the feasibility of the proposed approach in a manufacturing setting characterized by diverse product types and relatively low production volumes.
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POWDER BED FUSION FACTORY PRODUCTIVITY INCREASES USING DISCRETE EVENT SIMULATION AND GENETIC ALGORITHM

Ruba Al-zqebah[1], Matthias Guertler[1], Lee Clemon[1,*]

[1]University of Technology Sydney, Sydney, NSW, Australia

ABSTRACT

Additive manufacturing has emerged as a growing technology showing promise for the future of manufacturing, particularly in mass individualization production. In particular, powder bed fusion processes have achieved wide use across industries for both polymer and metallic components. However, due to the relatively slow deposition speed per unit mass compared to conventional methods, scheduling and production planning play a crucial role in scaling up additive manufacturing productivity to medium and higher volumes. Most research on additive manufacturing production scaling has focused on the quality of individually produced parts and control of printing technology rather than factory level management. In conventional production systems, several existing factory management and organization techniques exist including discrete event simulation and heuristic optimization methods. These have successfully improved productivity for conventional manufacturing but have not been examined in detail for the style of lot size 1 factories enabled by additive manufacturing. This paper introduces a framework combining discrete event simulation to evaluate factory dynamics and a genetic algorithm for further improvements through scheduling optimization resulting in makespan improvement opportunities for small scale powder bed fusion style factories. A particular case of multi-jet fusion machines and process flow are analyzed for a fixed ingest of 20 jobs. Worker and capital equipment levels are varied. Processing time for parts at each station represents a realistic dynamic system through discrete event simulation with data sourced from the historical performance of multi-jet fusion machines. The results show that bottlenecks move among workstations and process steps based on worker or capital equipment availability depending on which constraint is active. These bottlenecks are also dependent on the size of the facility shifting as the facility grows in size. Productivity improvement is limited when either the number of workers or capital equipment is fixed showing a resource-driven constraint. The combined discrete event simulation and heuristic optimization approach shows the trade-off of worker and capital equipment to achieve makespan improvements at varying facility levels. The addition of personnel or equipment removes some blockages and increases production with further gains achieved by scheduling optimization. Changes in resources provide productivity gains of 53% makespan improvement when adding the first worker with scheduling optimization using a genetic algorithm. This highlights the minimum level of manual processing required in powder bed fusion based manufacturing. The method developed here will help decision-makers in designing, staffing, and operating multi-jet fusion factories and inform similar studies on other powder bed fusion technologies.

Keywords: additive manufacturing, scheduling, discrete event simulation, multi-jet fusion

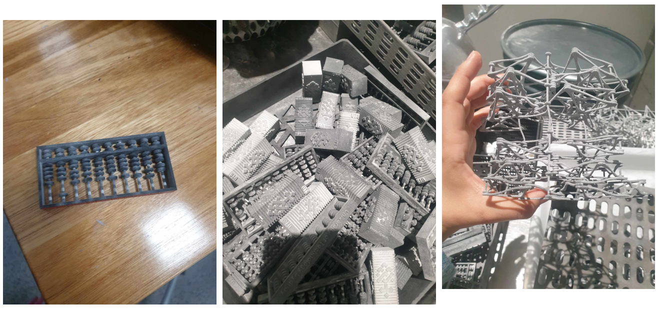
NOMENCLATURE

J set of jobs to be assigned $[units]$
j a job of p parts to be manufactured
n, p, m count variables
i, j, k indices for each machine, job, and process stage
P processing time
X assignment variable for scheduling
w makespan
S sequence of jobs
z size of the GA generation

INTRODUCTION

Powder bed fusion (PBF) [1], has become a viable option for industrial and commercial production. It has enabled the production of parts that are more complex, customized, and variable than conventionally manufactured parts. In this particular study, we focus on Multi Jet Fusion (MJF), which uses infrared lamps and a doping agent deposited by inkjet nozzles for fusing polymers together, and is classified in the PBF family of additive manufacturing processes per ISO/ASTM 52900 [1].In compari-

*Corresponding author: lee.clemon@uts.edu.au



(a) (b) (c)

FIGURE 1: SELECT EXAMPLE PARTS USED TO CALIBRATE PROCESSING TIME IN PRODUCTION STEPS

son to Material Extrusion[1], MJF is up to ten times faster with superior surface finish and more isotropic mechanical properties [2] leading to commercial adoption for tooling [3], production line components [4], and orthotics[5]. The recent announcement of HP's metal system, which is modeled on the MJF process has sparked interest in the industry for factory arranged production systems [6]. However, the scale-up of additive manufacturing for production-level fabrication is challenged by the low mass deposition per unit of time and the classic problem of high mix low volume products [7]. MJF systems allow for individual customization of parts built in the same batch leveraging the geometric freedom and enabling economic lot size 1 production. MJF is a layer-by-layer process, and the deposition rate is limited by the size of the deposition nozzles, the resolution of the print, and the properties of the material being used [8]. This can result in longer production times per unit compared to conventional manufacturing methods like injection molding. At a factory level, additional variables affect the total production time such as machine failure, worker availability, and shift time. When production quantities increase, the impacts of these variables become more significant and as the number of pieces of equipment and jobs increases explicit modeling becomes intractable. This type of scheduling problem is classified as an NP-hard problem, meaning finding guaranteed optimal solutions is not feasible, and thus stochastic or heuristic methods are required.

Scheduling and production planning methods in AM are still developing with a recent review indicating limited investigation into this topic and that most research was published within the last four years [9]. This indicates a need to adapt and update production planning methods from other production systems for the AM context. Prior studies on production planning in AM treated this challenge as a nesting problem to group parts in batches [10–13] and use a static representation of the production system [13–15]. Their objectives varied including minimizing production cost [12, 14], minimizing lateness [15], minimizing makespan [10], or maximizing profit and resource utilization [16]. Kucukkoc, et al. [13] added the consideration of creating batches on parallel identical and non-identical machines. Oh, et al. [17] investigated a heuristic algorithm to optimize the build orientation and 2D packing. Akram, et al. [18] examined the batching of identical parallel AM machines, aiming to meet distinct order deadlines while minimizing overall tardiness. They introduced both the mathematical framework for this challenge and a heuristic approach. The problem was deconstructed into two subproblems: first, the allocation of parts/jobs via part clustering linked to due dates, followed by job tardiness. This body of research focused on reducing the makespan with a static representation of the system and does not consider the stochastic and dynamic nature of a factory floor. Static implementations are unable to update with dynamic changes in worker or machine availability and setups. Thus, simulation methods that incorporate stochastic production challenges (like machine failures or worker absence) and queues are needed. Dynamic methods of simulating production flows can provide better insight into factory planning and management.

To overcome the challenges of a dynamic factory, adapting methods of production planning from conventional manufacturing could be beneficial. A seminal work in dynamic system simulation introduced Discrete Event Simulation (DES) to capture real-world variability for production scheduling [19]. DES has been successfully applied for bottleneck identification [20] and manual assembly [21]. DES has been a successful method for simulating solving complex queuing problems in conventional manufacturing [22–26], but has not been applied to additive manufacturing. Additive manufacturing is a lot size 1 production method with a flow shop type equipment arrangement. DES may be suitable for analyzing and improving AM process planning. DES does not iteratively perform optimization on its own. Instead, a suitable optimization method is also needed to provide further improvements in combination with DES. We apply Discrete Event Simulation integrated with a genetic algorithm to evaluate the impacts of factory level scheduling and capital resource allocation to address the highly stochastic variation AM and fill this gap.

This work presents a simulation-optimization approach to solve a scheduling and bottleneck identification problem in additive manufacturing for a powder bed fusion-based process which can inform factory planning and operations. This research extends productivity improvement methods from conventional manufacturing into the field of additive manufacturing showing the effectiveness of integrating GA with DES. Application of this method can enable companies to reduce their makespan and make informed decisions about equipment and staffing arrangements while reducing costs and improving customer service. This approach helps systematically analyze and identify the specific trade-off point between intended output performance and required machines and personnel as well as the contribution of intelligent scheduling.

PROBLEM STATEMENT

The production flow in an additive manufacturing facility is defined as a scheduling problem where n jobs, $j \in J = 1, 2, ..., n$, enter the facility in a processing window and need to be completed. Each job is comprised of p parts of varying dimensions and numbers. For example j_1 contains 5 parts j_2 has two parts j_n has p parts as $p_{j_1} = 5$ and $p_{j_2} = 2$. Each job is restricted

[1] also known as fused filament fabrication

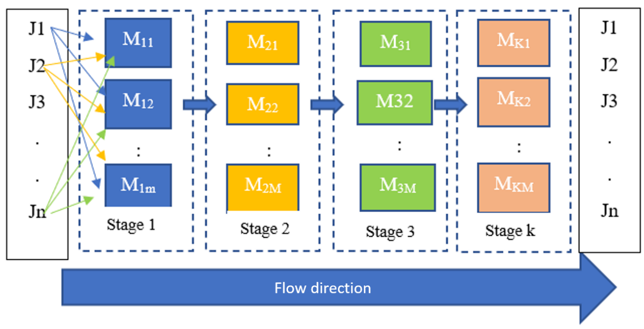


FIGURE 2: ASSIGNMENT STRUCTURE OF N JOBS TO M MACHINES THROUGH K STAGES USED TO SCHEDULE PRODUCTION

to a single batch. A batch is defined as a group of parts that are produced together in the 3D printer as a group at one time. The batch (or job) is then processed in subsequent stages as a collective unit.

Each job must progress through K processing stages. The sequence of stages is the same for each job, but the processing time for each stage varies depending on the features of the job (p parts, part dimensions, and part quantities). No restrictions have been made on the types of parts or their features other than those imposed by the machine used for fabrication. The processing time, $P_{j,k}$, of a given job, j at stage $k \in K$ is dependent on the number of parts and their design properties, such that $P_{j,k} = f_k(j)$. Processing time also includes any waiting time for worker availability, job setup, material transfer, and buffering.

The facility has m_k parallel machines in stage k such that any available machine, $M(k,i)$, in stage k can be assigned the next job. Define $M(k,i)$ as the machine with individual reference i in stage k. The presence and number of workers in the facility have an effect on the production speed. For some stages, a worker must be present to initialize the operation and for others, the worker must perform tasks throughout the duration of that processing stage. Thus, the layout of the facility and transit to and from each machine across all stages is included. Fig. 2 illustrates a general problem structure, depicting multiple stages and multiple machines within each stage. Jobs progress through the stages with the help of workers transporting them. In some stages, a worker must be present for processing. Additionally, the figure depicts multiple jobs that need to be allocated to these machines.

The goal is to minimize the total processing time for all n jobs $j \in J = 1, 2, \ldots\ldots, n$ with processing time ($P_{j,k,i} = \sum_k P_{j,k,i}$) on $M(k,i)$ parallel machines $i \in I = 1, 2, \ldots m_k$, where the machine assigned to the job at each stage may vary. This minimization considers the uncertainty and the dynamic nature of the additive manufacturing environment such as workers' availability, shift time, facility layout, and traveling distances.

To assign jobs to parallel machines, define the binary variable $X_{ijk} = [0,1]$ that takes the value 1 if the job is assigned to the machine in stage k and is 0, otherwise. Consider the following objective function to minimize makespan (w) of the sequence, similar to [27]:

$$w = \sum_{k=1}^{K} \sum_{j=1}^{n} P_{jk} X_{ijk} \tag{1}$$

In Eqn. 1 the makespan is defined as the completion time for all jobs where each job must be assigned to exactly one machine in each stage and must progress through all processing stages sequentially. We seek to find an order of such jobs and their allocations in each stage to minimize the total time for all available jobs to complete.

METHODOLOGY

The production simulation task is divided into two parts: (A) facility resourcing and (B) job scheduling optimization. For (A), the impacts of the number of workers and the number of capital equipment at the bottleneck location are sought. Then for each facility resourcing, a genetic algorithm is used to search for a schedule that minimizes makespan addressing (B). This work examines an example facility that exclusively uses the powder bed fusion (PBF) machines produced by Hewlett Packard (HP) called multi-jet fusion, which uses a series of inkjet nozzles for ink deposition and a heat lamp for thermal fusing. For (A) facility resourcing, a DES model of the factory is created and used to identify bottlenecks and evaluate worker and equipment utilization for each job schedule. The DES model captures additional information about the production to represent real-world production issues including worker shifts, worker travel, and machine downtime for each scheduling evaluation. For (B) job scheduling problem is solved to minimize makespan using a genetic algorithm and test candidate solutions given each variation in the number of machines and workers.

The MJF workflow comprises five main stages: (1) slicing, (2) printing, (3) cooling, (4) unpacking, and (5) sandblasting. Slicing is the process of converting the 3D drawing into instructions for the printer to action. Printing is the actual process of depositing powder and forming the parts. Cooling refers to letting the printed parts cool down to maintain dimensional accuracy and surface finish, it occurs in the building unit which contains the platform where the printed parts are constructed. The building unit in HP MJF machines can be removed from the printer for further post-processing such as cooling and unpacking which provides additional flexibility in scheduling allowing printers to become available quicker than other PBF processes. Unpacking is the stage of extracting the printed parts from the powder in building units using a vacuum. Sandblasting refers to completely removing powder from printed parts to achieve clean parts. This process is carried out by workers using a combination of airflow and sand. Other post-processing steps such as polishing and dying are possible but not included in this study. A digital model for production facilities was built to test the total production time of varying (a) parts (and processing times), (b) workers, and (c) machines using Siemens Tecnomatix Plant Simulation[28].

A test set of jobs was generated using historical data from a university additive manufacturing facility's HP Multi-Jet Fusion 4200 machine and initially randomly ordered. A range of factors influences the duration of each job stage. During unpacking and sandblasting, factors such as part geometry, packing density (number of parts), build height, material type, desired surface finish, and operator efficiency play a pivotal role in determining processing time. In this study, the number of parts was used as the primary determinant of processing time assuming all the parts have equivalent complexity within a job but vary among different jobs. To capture the variability in processing time for different parts' geometry, we have measured the processing time and simulated random values for unpacking between 2 min to 6 min and for sandblasting 2 min to 4 min per part. These values are obtained from the university's facility (Fig. 1). The objective is to demonstrate the varying time requirements of different jobs for scheduling purposes, rather than delving into the tool/material interface of the manufacturing process itself, thus approximated values informed by these measurements provide insight into realistic processing expectations. A set of twenty jobs and their processing times derived from this testing and variable range is listed in Tab. 1.

The type of production in this study is classified as flow shop production where all jobs follow the same route to completion but may vary in other aspects of their processing. First, a discrete event simulation model was built using Siemens Tecnomatix plant simulation to represent the real production process of printing parts using MJF printers including worker(s) and travel distance between machines. Next, a GA searches for the schedule that minimizes makespan, which improves productivity and reduces production costs. GA starts with defining valid inputs to establish the search space, in this case, it is limited to any order of the jobs, but a list that includes all jobs. This defines the population of possible solutions. Samples (sequences of jobs) are randomly selected from the population of all possible sequences. Each sequence selected by the GA represents a 'chromosome', or input string. Each chromosome is scored. Our fitness function is makespan, Eq. 1, to be minimized. The chromosomes that are highly score better (shorter makespan) than existing chromosomes are retained for the next generation (iteration) of the search. In this next generation, retained chromosomes have sections of job orders that are swapped with another chromosome. For example, Chromosome A has within it the sequence j4, j8, j10, whereas chromosome B has the sequence j10, j8, j4. These two segments of the schedule are swapped in place with each other to create two children, Chromosomes C and D, where Chromosome C is identical to Chromosome A except for the segment that was taken from Chromosome B of j10, j8, j4. In addition to crossover, top performers are mutated where a new chromosome is produced where two jobs are swapped in the global ordering of the original chromosome, e.g. j2 and j19 exchange places. Crossover and mutation produce new solutions that are close to the existing found solutions and thereby find local optima, leveraging the high-performance pieces of the parents. In addition to crossover and mutation is the stochastic search of random new sequences outside of the prior evaluated sequences. The best overall scoring chromosomes are retained until the convergence criteria or computational search time limit is reached [29]. Appendix B provides a visual depiction of the crossover and mutation processes.

Each DES setup is manually constructed by adding or removing machines and workers and then the GA schedule optimization is performed. Finding an optimal solution to the flow shop scheduling problem requires exploring a large number of possible scheduling combinations, which becomes increasingly difficult as the number of jobs and machines increases. The jobs can be assigned to the machines in (n!) sequences. Which is in the case of 20 jobs generating $20! = 2.4e^{18}$ possible orderings. The best solution given a limit on search effort using the GA is kept. We evaluate the makespan improvement by comparison to the original randomly generated sequence in Table 1, sequence (S): $s_0 = j_1, j_2, j_3, ..., j_{n-1}, j_n$. The GA creates a population of different sequences, each candidate sequence is generated randomly $S = [s_1, s_2, s_3......s_z]$. The jobs are assigned to the available machines according to their sequence with the priority rule of first in first out (FIFO) (Fig.2). The GA parameters are set according to trial and error (number and size of generation). Crossover and mutation are applied to produce additional new solutions. Then the value of these solutions is evaluated by computing their fitness value which is the makespan in Eqn. 1. The DES calculates the makespan of each tested sequence. Then, the best children (solutions) are used to generate additional possible solutions. This process is repeated through a present number of generations. A pseudo-code of the GA is provided Alg. 1. This study assumes:

- The processing time for each job is known a priori.
- Setup time is independent of the job sequence and is considered part of the processing time.
- It is not possible for a machine to process more than one job at a time.
- Each job contains a different number of parts, and the complexity (difficulty in extraction and cleaning) of parts is identical within a job.
- All machines are available at the beginning of the scheduling period.
- A 1% failure rate is incorporated into each printing machine.
- Printing time depends mainly on the maximum Z height in each job [9]. Derived from HP's specifications at a rate of 1 inch per hour ([30]) calculated on a layer thickness of 0.003 inches and thus 8.3 seconds for each layer. The build height in each job is generated randomly from 2 inches to 15 inches (maximum height on reference printer).

The objective is to minimize the total production time measured as the makespan, or total time to process all jobs in the schedule. The main two factors that affect makespan are job assignments and resource availability (workers, machines, etc.). The combination of DES and GA methods is applied to both different resource configurations. For the first setup, 3 printing machines are used with an input of 20 jobs. Unpacking stations are varied from 1 to 3, sandblasting stations from 1 to 2, and available workers from 1 to 3 (Tab. 2). Each arrangement (Exp) is evaluated using DES, the makespan is reported for the random default ordering and then the GA (Alg. 1) is used to optimize the scheduling order for the factory setup. GA has been parametrized based on running various experiments until the best fitness values are achieved, which involves adjusting the number and size of generations. Appendix C shows the parameters that were used.

TABLE 1: GENERATED LIST OF 20 JOBS FOR PROCESSING WITH PROCESSING TIMES IN EACH STAGE

Job	Number of parts (units)	Max Z height (inches)	P-Slicing (min)	P-Printing (min)	P-Unpacking (min)	P-Sandblasting (min)
1	34	15	68	900	204	102
2	57	9	114	540	228	114
3	8	2	16	120	32	32
4	33	13	66	780	132	132
5	11	11	22	660	44	22
6	41	9	82	540	164	123
7	37	9	74	540	222	148
8	28	13	56	780	112	112
9	54	12	108	720	216	216
10	39	4	78	240	234	156
11	54	10	108	600	324	108
12	8	13	16	780	40	16
13	29	7	58	420	116	87
14	10	8	20	480	50	30
15	60	3	120	180	240	180
16	51	5	102	300	255	153
17	48	11	96	660	192	192
18	44	10	88	600	176	176
19	13	11	26	660	52	26
20	14	6	28	360	84	28

Algorithm 1 GENETIC ALGORITHM

Require: $S_0 = \{j_1, ..., j_n\}$ ▷ available jobs
$\mathbf{S}_{initial} = \{S_1, ..., S_q\}$ ▷ generate initial candidates
Execute DES for $S_r \in \mathbf{S}$
Compute $w = \sum_{k=1}^{K} \sum_{k=0}^{n} P_{jk}, X_{ijk}$
for N generations **do**
    Mutate best performers, add to pool
    Crossover best performers, add to pool
    $\mathbf{S}_{new} = \{S_1, ..., S_q\}$ ▷ generate new candidates
    $\mathbf{S} = [\mathbf{S}, \mathbf{S}_{new}]$ ▷ add candidates to pool
    for each $S_r \in \mathbf{S}$ **do**
        Execute DES for S_r
        Compute $w = \sum_{k=1}^{K} \sum_{k=0}^{n} P_{jk}, X_{ijk}$
    Order S_r by shortest w to longest
    Retain best t performers
return $\mathbf{S}, w(\mathbf{S})$

The makespan includes working time and non-working hours. There were two breaks (a short break of 15 minutes and a lunch break of 45 minutes) during the shift (8 hrs/day).

RESULTS

With a single worker, the makespan remains unaffected by increased other resources. For example, adding an extra unpacking station to this scenario kept the makespan constant, see Exp1 vs Exp2 (Tab.2). Thus, equipment resources are not constraining production in this scenario. However, with the addition of one extra worker without scheduling optimization, the makespan was reduced up to 30% (Exp1, Exp3) with 3 machines, indicating that the bottleneck in this arrangement was the availability of workers.

Introducing an unpacking station and performing the GA scheduling optimization to the two workers' setup dropped the makespan 31% from Exp3 before GA to Exp5 after GA. This results in a total improvement of 52% improvement from Exp1 without the GA scheduling optimization to Exp5 after the scheduling optimization. Adding an extra sandblasting station did not significantly change the makespan, 0.6% (Exp3, Exp4).

In certain instances, the application of the genetic algorithm schedule leads to a *more significant reduction in the makespan than adding extra workers or equipment*. For instance, in Exp5, the makespan was reduced 25% from 12:02:44:41 to 9:03:31:45 after applying the GA. Moving from Exp5 to Exp10 by introducing an extra worker, an extra unpacking station, and an extra sandblasting station only reduced the makespan by 0.4% to 12:01:30:28 without applying the GA scheduling optimization. The total improvement from Exp1 to Exp10 is 53%. Figure 3 shows a snapshot of the activities for workstations and machines in Exp5 before the GA scheduling. We see the worker break periods are deemed paused time, and 'unplanned' refers to time without a worker on shift. These variations in availability and the simulated job sequence give realistic factory performance which is also unique to the job sequence. Given portions of MJF manufacturing can be unmanned, the GA search preferences schedule longer tasks that do not require a worker to begin toward the end of a shift.

The makespan improved significantly after adding an additional unpacking station, but a greater improvement was observed by adjusting the job schedule through the GA (Table 2). This table displays the average values obtained from running the DES model five times. The individual values for each replicate are provided in Appendix D. The GA ran for 100 generations with five candidate solutions in each generation. The GA largely con-

TABLE 2: MAKESPAN RESULTS BEFORE AND AFTER SCHEDULING OPTIMIZATION FOR VARIOUS FACTORY RESOURCES USING 20 JOBS

Exp (ID)	Workers (#)	Unpacking (#)	Sandblasting (#)	Makespan (dd:hh:mm:ss)	Makespan GA (dd:hh:mm:ss)	Reduction by GA (%)
1	1	1	1	19:02:25:36	16:05:50:26	15
2	1	2	1	19:02:25:36	16:05:50:26	15
3	2	1	1	13:07:33:00	12:02:37:36	9
4	2	1	2	13:05:33:32	12:02:42:01	9
5	2	2	1	12:02:44:41	9:03:31:45	25
6	2	2	2	12:01:30:21	9:02:58:29	24
7	3	1	1	13:07:33:00	12:02:37:36	9
8	3	2	1	12:02:13:35	9:01:36:08	25
9	3	3	1	12:02:05:47	9:01:29:52	25
10	3	3	2	12:01:30:28	9:01:10:46	25

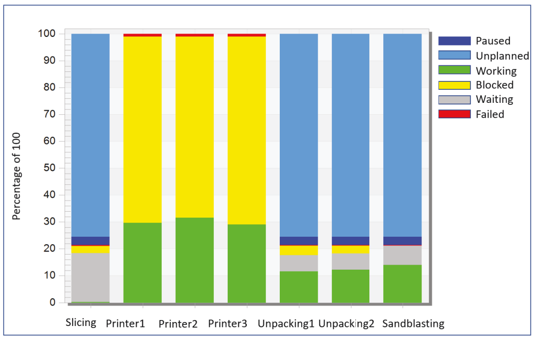


FIGURE 3: PROCESSING STATISTICS OF EACH STATION BY ACTIVITY IN EXP 5 (TAB. 2) PRIOR TO GA SCHEDULING OPTIMIZATION

TABLE 3: MAKESPAN IMPROVEMENT FROM BOTH DES AND GA COMBINED AS A PERCENTAGE (%) FOR 100 JOBS

Workers \ Units	1	2	3
1	4	5	5
2	49	49	49
3	50	64	66

verged after 16 generations, with only a small improvement found after 60 generations, as shown in Fig. 4).

The best performing assignment orders were those with the most resources and use of GA: Exp 8, 9, and 10. Exp 8 saves approximately 3 working days which is a 25% reduction in manufacturing time and uses the fewest resources for comparable performance. This represents a significant reduction in makespan for a production facility, saving more than a day a week in time without increasing resources.

In order to assess the scalability of GA in minimizing makespan in this environment, the number of jobs was increased from 20 to 100 (Fig. 5) for a consistent configuration (3 workers, 3 printers, 1 building unit, 3 unpacking stations, and 3 sandblasting stations). The scaling shows that increasing the problem size leads to greater improvements from GA scheduling, up to 66% from the default list (Table 3).

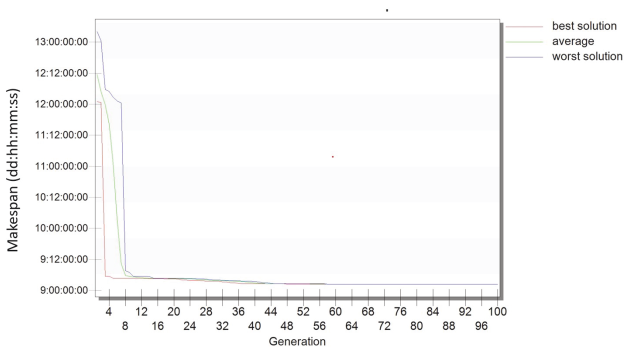


FIGURE 4: CONVERGENCE CURVE OF GENETIC ALGORITHM IN REDUCING THE MAKESPAN WITH INCREASING GENERATIONS

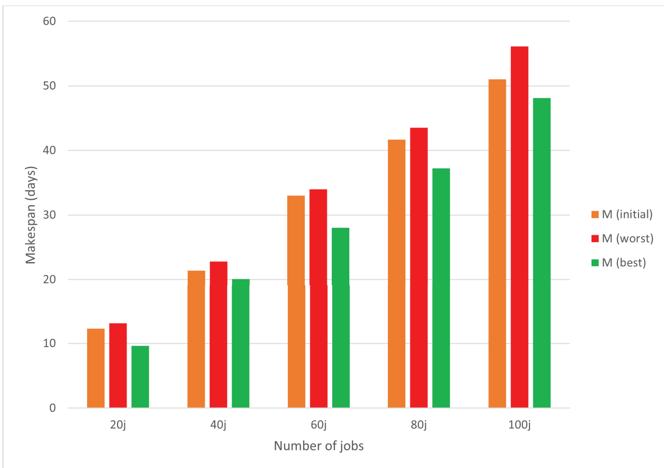


FIGURE 5: THE VALUE OF MAKESPAN AT DIFFERENT SIZES OF JOBS SHOWING THE INITIAL VALUE OF MAKESPAN (M INITIAL) AND THE BEST AND WORST SOLUTIONS OBTAINED BY GA (M BEST AND M WORST)

DISCUSSION

The simulation model was developed to explore improvement opportunities in a multi-jet fusion factory through a combined discrete event simulation and scheduling optimization using a genetic algorithm. The developed method of combining DES and GA optimization showed improvement opportunities from both industrial resource changes, like adding more machines and scheduling improvements. This highlights the multiple dimensions of production system design addressed by this combined approach which is not provided by either DES or GA when used in isolation. The evaluated job scaling also illustrates opportunities and gives guidance on scaling up MJF to factory-level production. For example, temporary job shocks can be managed effectively through scheduling optimization which was able to reduce the makespan by up to 25% in the 20 jobs load. The objective to minimize total production time (makespan) through combined DES production planning and scheduling in additive manufacturing offers a path for the scale-up of production volumes. The introduction of this approach overcomes problems associated with other scheduling works for AM factory planning, which rely on assumptions of static systems and simplifications that may not capture real-world scenarios. DES allowed simulation of worker movements, downtime, and shift schedules as well as dynamic bottlenecks. The simulation experiments show the necessary number of workers is contingent upon the quantity of unpacking stations and building units present in the facility. This is due to the manual unpacking process, which can obstruct the flow of printed parts from the printers. Moreover, if the number of workers falls short of the desired number, adding extra equipment may prove to be redundant and lead to increased costs without improving the makespan. For instance, when a single worker is already present adding more building units (2 to 3) will not lead to any improvement. Because the building units in this case are not the bottleneck. However, the addition of extra units could be more useful in cases where there are more workers, roughly scaling with the number of building and unpacking units. If there are insufficient workers, adding more equipment does not add value.

The example facility used HP Multi-Jet Fusion 4200 machines with all major production tasks included from file preparation through to cleaning printed parts. This example facility can be used as a representative of a polymer factory with many parallels to metal machines. The biggest improvements from a single resource addition are observed when adding the second worker in all production unit arrangements with up to 49% reduction in makespan with the 100 jobs case. For the tested number of jobs, there appears to be a decreasing marginal benefit with the addition of more capital resources as the factory scales up.

A failure rate is included which adds unplanned downtime that is not captured in static analyses but offers the genetic algorithm some additional search space. In a continuous job arrival mode using the same job list on loop, the resource statistical results show that the printers have a low working time due to blockages (Fig. 3). The main reason for this blockage is the cooling time is about 24 hrs which is done in the building unit so the printer can't be run until the the building unit is removed and a new one is installed. The printers do not have unplanned or paused time by definition because they could be run without a worker present, i.e. 24 hours per day. However, printer starts are limited by the availability of a worker to commence a job and downstream processing of printed parts. This suggests that multiple shifts could further increase production and reduce or eliminate the high percentage of the blockage shown in the activity statistics.

The GA schedule perturbation showed improved makespan for most of the experiments, up to 25%. However, in a couple of cases, it did not find a better job order, such as when there were 2 workers with 2 or 3 unitsFor these scenarios, the default job order may be a sufficiently good order given the worker availability constraints. The initial job order was randomly determined and is not the worst possible job ordering, so it may also be that this initial random order was a pretty good schedule. Though it is possible that a much longer search time may find some additional improvement in the job order. Processing time and complexity of the produced parts were assumed to not vary with individual part geometry, therefore the only factors that affected the processing time at any station were the number of parts and their maximum build height in the building unit. This provided sufficient variation in job processing time for this level of simulation for factory management. Additional research in packing arrangements[17, 31] or toolpath optimization[32, 33] was not in scope in this study and would merely inform the printing time for further simulations using the presented approach. This assumption is easily adjusted for specific use cases by future practitioners. The effectiveness of combining discrete event simulation with a genetic algorithm may vary in magnitude for different printing equipment or factory layouts.

This framework will help decision-makers design and maximize production in current and future factories for the AM industry. Existing factories can use this approach to understand their system and needs in a virtual environment without interrupting the production line and to test different scenarios before implementation.

CONCLUSION

This work introduces a simulation optimization-based analysis to support additive manufacturing planning and scheduling for factory production based on combining discrete event simulation and a genetic algorithm. DES was used first as an evaluation tool to analyze the performance of different resource configurations and to identify bottlenecks. Subsequently, GA was used to further improve the makespan by reordering the available jobs. The case studies revealed that the bottleneck was often the worker availability, suggesting matching workers closely to the number of unpacking stations. Adding an extra worker led to a significant reduction in makespan by up to 53% for 20 jobs. The DES experiments identified the makespan reduction with either the addition of more workers, more building units, or a combination. Integrating GA into the DES model for scheduling introduced a further reduction in the makespan by up to 25%. However, it also showed adding extra resources may prove to be redundant and lead to increased costs without improving the makespan if the number of workers falls short of the desired number. Instead, it helps to find the right balance between the number of workers and the number of different equipment for a given job set. Determining this balance can occur through using the methodology developed in this work as a production planning tool for dynamic production systems. This can help decision-makers determine the proper number of resources to deliver parts in time and how to allocate limited resources in the most efficient and flexible way.

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CHAPTER 5

PAPER 3: A NOVEL APPROACH AND CASE STUDY TO ASSEMBLY LINE BALANCING USING DES AND HEURISTIC METHODS

This paper addresses the third research question, "*What is the effectiveness of combining DES with heuristic methods to solve assembly line balancing problem (ALBP) in Low -Mix High-Volume (LMHV) Manufacturing?*" Answering this research question provides a proof of concept for the proposed approach in a production environment that is greatly influenced by demand fluctuations, leading to an uneven distribution of workload across workstations and consequently reducing overall resource utilization. The paper is organized as follows: It begins with an introduction to the assembly line balancing problem, providing an overview of methods used in the literature to address it and offering background information on various assembly line types. The research methodology, along with case studies, is then presented to elucidate the approach. Three heuristic methods are implemented alongside DES. The implementation details are analyzed and discussed, and finally, the paper concludes with a wrap-up.

Paper status: *submitted to the journal of Production and Operations Management*

A novel approach and case study to assembly line balancing using discrete event simulation and heuristic methods

Abstract:
Assembly line balancing can help reduce idle time, maximize throughput, identify bottlenecks, and improve the flow of production when the workload is distributed evenly across workstations. This allows manufacturing companies to reduce waste and improve overall productivity. In this study, we present a novel approach to increase the efficiency and throughput of the assembly line through the combination of heuristic task allocation methods and discrete event simulation (DES). We applied our method in a case study for an enclosure manufacturing company. We started by collecting data from their current line setup. Then, three heuristics techniques for task allocation: (1) Largest Candidate Rule (LCR), (2) Ranked Positional Weight (RPW), and (3) Kilbridge and Wester Column (KWC) have been used to generate alternative preliminary solutions. We then build a digital model matched to the existing line to simulate the real-world system and adjust this model to propose and evaluate various alternative improvement scenarios. The results show that LCR and RPW assign tasks in a similar manner, while KWC allocates tasks differently. Despite these variances, all three heuristic methods demonstrate comparable improvements, increasing line efficiency from 72.8% to 76.4%. Applying DES through implementing "what-if" analyses to the initial solutions obtained by heuristic task allocation methods led to an increased line efficiency of 91.6%. Therefore, integrating DES with heuristic task allocation methods appears to be a promising strategy for decision-makers seeking substantial enhancements in line efficiency, especially compared to the use of heuristic methods alone.
KEYWORDS: assembly line balancing, discrete event simulation, heuristic methods

5.1 Introduction

The Assembly Line Balancing Problem (ALBP) is a central challenge in manufacturing that often emerges due to an uneven distribution of workload across workstations [78]. This unevenness results from changes in demand, the introduction of new products, unforeseen equipment malfunctions, or inefficient management and process control [79]. Thus, a crucial aspect of ensuring a streamlined operation of production processes involves equal task allocation across workstations while adhering to certain technological constraints. This task allocation strongly affects metrics of the overall system performance, such as production time, throughput, resource utilization, and system efficiency.

The fundamental principle of assembly line problems involves distributing tasks among stations in a sequential order while respecting the precedence relationships and obtaining certain efficiency measures [80]. ALBP is considered an NP-hard problem due to the extensive possible combinations of tasks and workstations [81]. The identification of optimal assignments necessitates the evaluation of each possible combination, which is impractical for large sizes of assembly lines. Salveson was the first to discuss this topic in 1955, proposing linear programming as a solution [66]. Subsequent research has been extensive, and scholars have suggested solutions under four primary categories: mathematical optimization techniques, heuristic methods, metaheuristics, and simulation [14]. The quality of solutions varies among these methods. For instance, mathematical programming provides optimal solutions but requires significant time for computation. Conversely, the other categories offer satisfactory or near-optimal solutions within a feasible time but might not discover globally optimal solutions. However, heuristic and metaheuristic methods, given their static nature, may not fully represent the dynamic aspects of assembly line systems. Meanwhile, simulation methods excel in modeling complex and dynamic environments but are not efficient standalone optimization tools.

To the best of our knowledge, existing literature did not attempt to solve this problem by combining DES alongside heuristics; the majority used DES as an evaluating tool only. This study aims to answer the following research question: ***What are the potential benefits of integrating Discrete Event Simulation (DES) with heuristic methods for ALBP optimization?***. Our investigation focuses on the comparative effectiveness of this integration as opposed to prior work, which uses each method as an alternative or evaluation tool only for solving ALBPs. We conducted a case study involving an assembly line to address this research question and employed three heuristic methods. Then, we used the results (number of workstations and task assignments) to integrate them into the DES model, analyze the solution, and propose various enhancement scenarios guided by DES analysis. Finlay compares the line efficiency and throughput between the heuristic and raised scenarios.

A background of ALBP types and a review of relevant literature in this space is presented in section 2. Section 3 provides a detailed description of our research methodology. Our findings are presented and discussed in Section 4, while Section 5 summarizes our concluding remarks.

5.2 Background

ALBPs are primarily divided into two types based on the underlying assumptions: Simple Assembly Line Balancing Problems (SALBPs) and Generalized Assembly Line Balancing Problems (GALBPs). If the following assumptions hold true, the problem can be classified as a SALBP. These assumptions include [82]: the processing time for each task being known, and precedence relationships are well established. It is also assumed that all tasks need to undergo processing and that the costs related to each workstation are roughly equivalent. Tasks are individable and cannot be spread across two or more workstations. The flexibility of task assignment is maintained with the provision that any workstation can handle any task. In terms of operational capacity, it is understood that the time taken at a workstation must not exceed the cycle time. Lastly, the SALBP assumes that assembly systems are structured to cater to a single unique model of an item. If any of these assumptions do not apply, the problem falls under the category of GALBPs [83]. A significant portion of the existing research has focused on SALBPs. These have been divided further into two main categories based on their objective, called SALBP-1 and SALBP-2 [84]. The primary goal of SALBP-1 is to minimize the number of workstations within a given cycle time, while SALBP-2 aims to minimize the cycle time given a fixed number of workstations. Assembly lines can be divided into two primary categories based on the arrangement of workstations: straight lines and U-shaped assembly lines [85]. In a U-shaped line, workers can operate at both the start and end of the production line. In contrast, straight assembly lines limit workers to operating only along the line. Additionally, straight assembly lines can assign tasks once their predecessors have been assigned to stations. In contrast, U-shaped lines can allocate tasks in either direction, implying that the number of stations required for a U-shaped layout will never exceed that required for a traditional straight-line layout [85].

5.2.1 Analytical methods

Analytical methods seek to define the ALBP setup explicitly in a set of mathematical formulas and equations, which are solved. The objective is to minimize a certain performance measure, such as cycle time, workstations, or production rate, subject to a set of constraints. The first step in mathematical programming is identifying the problem variables, such as the number of tasks, workstations, assignment condition variables, cycle time, and precedence relationships. Next, the objective function and constraints are defined based on the problem requirements and constraints, such as the available resources, task times, and precedence relationships. Past efforts to solve ALBP with this approach include dynamic programming [86], branch and bound method [87], and mixed integer programming [88]. Although analytical modeling can provide an exact optimal solution for the ALBP, it requires significant computational resources and may not be feasible for many complex and dynamic problems found in practice [14]. Therefore, heuristic and metaheuristic techniques are often used as a compromise between solution quality and computational complexity.

5.2.2 Heuristic and metaheuristic methods

Heuristic and metaheuristic methods are simplified optimization techniques that are used extensively to solve ALBPs [84]. Heuristic methods are often problem-dependent, meaning that a suitable method is defined as narrowly applicable to a particular problem and may or may not be generalized. The most common heuristics used for ALBPs are the largest candidate rule (LCR), rank position weight (RPW), and Kilbridge and Wester Column (KWC) methods [80]. These techniques use priority values calculated from task completion times and the precedence relations. In the LCR method, tasks are arranged in descending order according to their duration, the task with higher processing time has higher priority to be assigned first if it does not violate the precedence constraints and does not lead the total workstation time to exceed the cycle time. The tasks continued to be added to stations until all tasks were assigned. In comparison, RPW starts by computing the RPW for each task by summing the processing time for the task and all the tasks that follow it on the precedence diagram. After that, the tasks are arranged in descending order according to their RPW number. The tasks with higher RPW have the priority to be assigned first to the workstation. KWC assigns tasks to stations according to their location in the precedence diagram. The priority of assignment is the task with the highest processing time, which is located in the commencement columns. To assign tasks for the workstations, the selection starts from the top of the list considering that the summation of processing time for the located tasks into the workstation shouldn‚Äôt increase the cycle time as well as the precedence constraints. In general, to solve any assembly line problem, The first step is breaking the assembly process into tasks and computing each task processing time. If the problem type is ALBP-1, the first step is to compute the cycle time which is the product’s completion time, or the total time to move the product from one workstation to another, and then calculate the theoretical number of workstations according to the following formulas [80]:

$$\text{Cycle time (C)} = \frac{\text{Available time per day}}{\text{Desired throughput per day}} \tag{5.1}$$

$$\text{Theoretical number of Workstations (W)} = \frac{\text{Total task time}}{\text{Cycle time}} \tag{5.2}$$

Afterward, heuristic methods are employed to assign tasks to the stations in order to minimize the total number of workstations. The assignment process is then evaluated using performance measures such as lead time, idle time, and line efficiency. Using the following formulas [80]:

$$\text{Lead time (L)} = \text{Number of workstations (N)} \times \text{Cycle time (C)} \tag{5.3}$$

$$\text{Idle time (I)} = \sum_{i=1}^{N} (\text{Cycle time} - \text{Workstation time}_i) \tag{5.4}$$

$$\text{Line efficiency (E)} = \frac{\text{Total task time}}{\text{Lead time}} \times 100\% \tag{5.5}$$

Metaheuristic methods are similar to heuristic methods in that they do not seek to capture all problem aspects explicitly nor find globally optimal solutions. However, metaheuristics use more sophisticated techniques to search for good solutions and are more generalizable than problem-specific heuristics. Metaheuristics starts with an initial solution and then uses randomized or stochastic methods to explore the search space for better solutions, keeping the best-found solution. Many researchers conducted either heuristic or metaheuristic methods. For example, [89] proposed combining multiple heuristic methods to optimize a single model assembly line. Similarly, [90] introduced an algorithm based on integrating ant colony optimization with a genetic algorithm for mixed-model assembly line balancing problems taking into consideration the sequence-dependent setup times between tasks. Other researchers built a comparative evaluation between existing optimization methods such as [14]. They compared the performance of eight heuristic methods in balancing a large-scale automotive enterprise. According to their finding, there was a slight variation in the heuristic results. At the same time, other researchers such as [58] found that some heuristics perform better than others according to the problem constraints in terms of the quality of the solution and the computation time. In this study, we compared our approach with the three most widely used heuristics (LCR, RPW, and KWC).

5.2.3 Simulation

Simulation has been used in solving ALBP. Simulation starts with building a virtual model that represents the real-world production system. This model is then used to observe the performance of the assembly line under various configurations. Simulation can help identify the bottleneck stations, inefficient areas, and opportunities for improvement. Moreover, it can be used to test different scenarios virtually without disrupting the actual production process. However, it is not an optimization tool on its own [91]. It simply computes system behaviors under specified conditions but could be used with other methods for iterative optimization. [65] proposed a heuristic algorithm for line balancing and used simulation to evaluate the performance of the heuristic under various line configurations. [67] used the Grouping Evolution Strategy (GES) algorithm to minimize the number of workstations and smoothness index and maximize the line efficiency for two configurations: straight and the U-shaped assembly line. Then DES to capture the stochastic behavior of the production line for both layouts. [68] used simulation as an evaluation tool for the output of a genetic algorithm to enhance productivity, line efficiency, and tardiness. [69] integrated simulation to the genetic algorithm for solving mixed model assembly line problems. Their approach focuses on integrating task assignments using GA and sequencing decisions using simulation. Their goal is to minimize the cycle. In contrast, our research is geared towards minimizing the number of workstations and maximizing resource utilization while keeping the cycle time fixed. [66] used two heuristic methods called Probabilistic Line Balancing Technique and Largest Set Rule Algorithm to balance multi-model assembly line, then they used simulation as a supported tool to compute time losses and queues.

Summary of the previous work

Previous research in solving ALBP focused on comparing existing methods or combining several techniques to achieve higher performance levels. The use of discrete event simulation was focused on evaluating other proposed heuristics and approaches. DES has very little prior use in the loop as part of the optimization strategy for ALBP. Thus, using DES alongside heuristic methods to modify the production line and applying "what-if" scenarios may offer new insights and further increase productivity. In our work, we introduced this concept of combining DES and heuristic optimization through a real-life case study. We collected production data and then used several heuristic methods to produce initial solutions. Next, those solutions entered into a simulation model to investigate the probability of achieving further optimization. DES model helps by identifying the bottleneck station, which can not be captured by heuristics. This was followed by proposing several improvement scenarios to reduce the effect of bottlenecks, such as reassigning tasks to other stations and changing the layout and number of workstations. Ending with selecting the most effective solution. [92] used simulation as an alternative tool and compared its performance to a heuristic method called 'Hoffman'.

5.3 Research Methodology

To address our research question. We propose a hybrid approach based on integrating the heuristic methods with the DES. We analyze the current state, find the bottleneck, and improve resource utilization through a hybrid line balancing technique, which leads to enhanced overall productivity. To achieve this, we proceed through the following three phases:

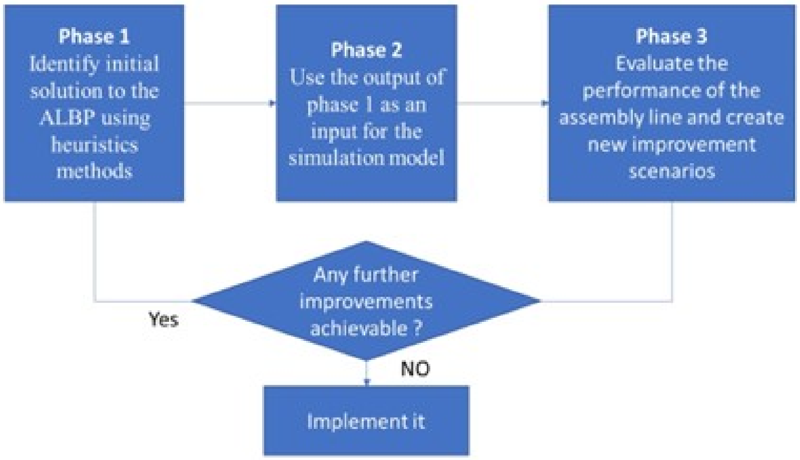

Figure 5.1: Iterative optimisation phases for ALBP informed by heuristic arrangement and updated from DES outputs..

1. First we used the heuristic methods to determine the required number of workstations to match the desired demand (throughput) and identify how the tasks should be assigned to these workstations. These methods were conducted manually and in a parallel manner. Each method's performance has been assessed based on line efficiency and throughput to identify the optimal method, which will be employed in subsequent stages to achieve the best solution.

2. We developed a digital model of the production process, using Tecnomatix Plant Simulation software [93] to mimic the solutions created by each method. This software was chosen among other simulation tools because it is user-friendly, easy to connect to other tools, and has advanced analysis and visualization features such as a bottleneck analyzer, animation, and statistics. These features allow users to examine the results of simulations and make informed decisions about how the system can be optimized [94].

3. Then we raised multiple improvement scenarios based on the DES model that involve changes to the assembly line layout, number of resources, and the allocation of tasks to resources until we achieve higher line efficiency.

In summary, the integration process commences with the initial computation of a theoretical solution in isolation, followed by the creation of a digital model that accurately reflects the current state of the assembly line. This digital model is then employed to apply the theoretical solution to the DES model. Simultaneously, an iterative process is initiated to evaluate and refine these solutions through the DES model until a satisfactory solution is achieved (Figure 5.1).

Case study

A company for production enclosures in Australia was selected for study due to its operational setup involving assembly lines. It has three assembly lines designed for enclosures of different types and sizes. In this study, the chosen line was dedicated to producing small-size enclosures. The line was experiencing challenges in meeting the desired demand. Data was collected on that line, such as recording all tasks required to assemble small-size enclosures, the processing time for each task, tasks' relationships, the number of workers available, working and non-working hours, as well as the layout of the production line. The field visit was carried out to this company on 15 November 2022, and the observations of the assembly line were made for 2 days. The assembly process was broken down into a set of tasks. The duration of each task was measured by stopwatch and recorded in a notebook. The assembly process commences with the placement of the enclosure's main body onto the assembly conveyor. Subsequently, a series of tasks are carried out, including the attachment of screws, joints, and doors, the application of stickers, the insertion of joint kits, and the preparation of the enclosure for packaging. Table 5.1 presents a summary of the tasks involved in producing the enclosure. It includes tasks' labels, descriptions, the precedence relationship between the tasks, and the average processing time for each task. The precedence relationship is visualized in Figure 5.2. The assembly line contained four workers, and it ran one shift of 8 hrs and 30 minutes, including a 30-minute lunch break and two short breaks of 15 and 10 minutes (the break time used to be deducted from the actual working hours). The line's average throughput was 252 enclosures per day, falling short of the target of 400 enclosures. To enhance the line's productivity, we implemented our method and evaluated its performance against three existing heuristics. The results obtained are shown and discussed in section 4.

Table 5.1: Assembly line task list with precedence dependencies, and measured task time

Task label	Task description	Predecessor	Avg Task time (sec)
A	Load the part	-	60
B	Screw 4 screws	A	28
C	Add stickers	A	10
D	Mount the joints	A	40
E	Mount the door	D	60
F	Paper taps to close the door	E	10
G	Packaging box preparing	-	30
H	Fill the box with joint kits	F, B	20
I	Glue the box	H, G	15
J	Transport the part	I	40
Total			313

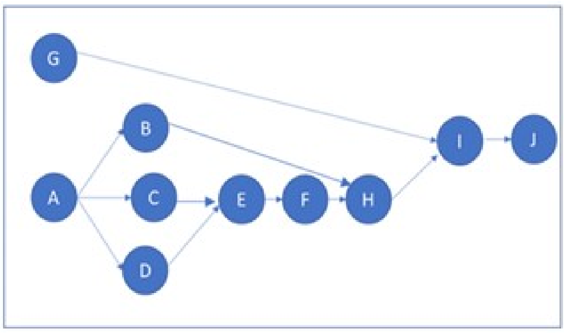

Figure 5.2: Precedence diagram of the tasks

5.4 Results and Discussion

This section presents the outcome of applying three heuristic techniques in task allocation to workstations, including the necessary count of workstations and other performance indicators such as line efficiency and productivity (Section 5.4.1). Additionally, this section highlights the integration of DES with prior methods and suggests alternative enhancement scenarios that can lead to further improvement when compared to the utilization of heuristic techniques alone (Section 5.4.1).

5.4.1 Heuristic techniques (phase 1)

The first step in ALBP-1, regardless of the type of heuristic method(s) used, is to compute cycle time and the number of workstations. The cycle time was calculated using equation (5.1) by dividing the available working time per day by the desired throughput, resulting in 455 minutes / 400 parts = 68.25 seconds/part for the case study. Similarly, using equation (5.2), the ideal number of workstations was computed as 5 workstations. However, in reality, the realized number of workstations depends on the specific requirements and constraints of the problem. To determine the realized number of workstations and how tasks were assigned to workstations, we compared three heuristic methods: LCR, RPW, and KWC.

Largest Candidate Rule (LCR)

In this method, the tasks are arranged in descending order according to their required time (Table 5.2). This method assigns tasks to six stations, as shown in Figure 5.3. Task A was assigned to Workstation 1, tasks D and B were assigned to Workstation 2, tasks C and G were assigned to Workstation 3, Task E was assigned to Workstation 4, tasks F, H, and I were assigned to Workstation 5, and finally, tasks J was assigned to workstation 6.

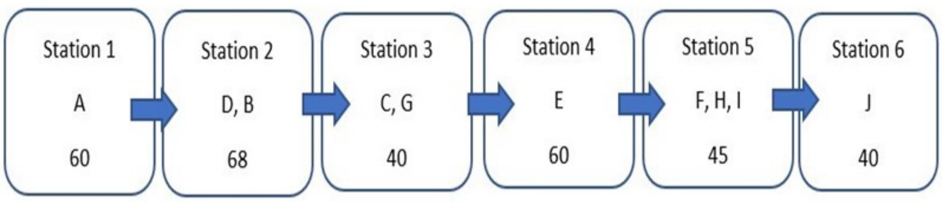

Figure 5.3: Tasks assignment with total workstation processing time according to LCR

Table 5.2: Tasks arrangement in descending order

Task label	Predecessor	Avg task time (sec)
A	-	60
E	D	60
D	A	40
J	I	40
G	-	30
B	A	28
H	F	20
I	H, G	15
C	A	10
F	E	10

Rank Position Weight Technique (RPW)

In the RPW technique, the tasks were arranged according to their computed weight (Table 5.3). These Weights were calculated by the cumulative sum of the current task and all subsequent tasks. Then tasks were assigned to workstations following this rule procedure (Figure 5.4)

Figure 5.4: Tasks assignment with total workstation processing time according to RPW

Kilbridge and Wester Column Technique (KWC)

After implementing the KWC method, it was determined that a minimum of six workstations is required. Represented by the black borders (Figure 5.5), light blue circles represent the possible task's location in the columns. The table labeled as Table 5.4

Table 5.3: Tasks ordered according to their RPW

Task label	RPW	Predecessor
A	223	-
D	155	A
C	145	A
E	113	C, D
B	85	A
G	85	-
F	85	E
H	75	F,B
I	55	H
J	40	I

displays tasks assigned based on their respective columns. This grants priority to tasks in the commencement column to be selected and assigned to workstations.

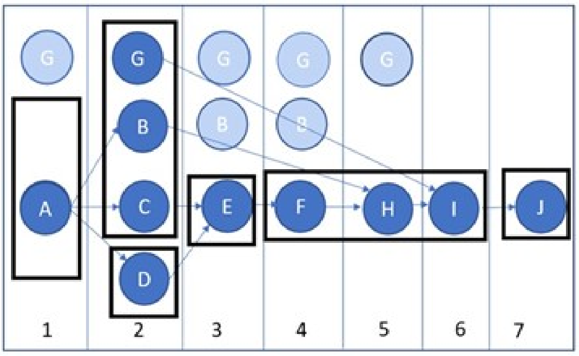

Figure 5.5: Tasks arranged into columns for KWC method

Following KWC procedures, the final assignment of tasks to workstations and the total processing time for each workstation are shown in (Figure 5.6).

In this case study, both LCR and RPW produce the same task assignments (Figure 5.3, Figure 5.4). While the KWC method allocated tasks differently in stations two and three; workstation 2 grouped tasks G, B, and C. Workstation 3 takes only task D (Figure 5.3). However, these three techniques required 6 workers to meet the demand. This results

Table 5.4: Arranging tasks according to their column

Task label	Column	Task time	Predecessor
A	1	60	-
G	1,2,3,4,5	30	-
D	2	40	A
B	2,3,4	28	A
C	2	10	A
E	3	60	C, D
F	4	10	E
H	5	20	F, B
I	6	15	H
J	7	40	I

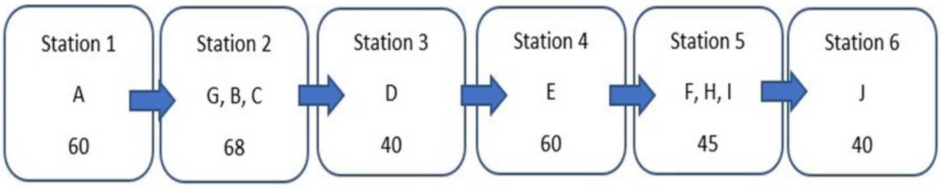

Figure 5.6: Tasks assignment with total workstation processing time according to KWC

in the same lead time, idle time, and line efficiency, which is equal to 97s, 409.5 s, and 76.4% respectively. While the heuristic approach does help in aligning with the desired throughput and improving efficiency, the question arises: Is this solution the most optimal one? Considering the use of heuristics, we further explored opportunities for additional enhancements by incorporating DES in Section 5.4.1.

5.4.2 Discrete Event Simulation (DES)

5.4.2.1 Evaluate the heuristic method using DES (phase 2)

A digital model was built using Tecnomatix plant simulation software to test the solutions proposed by LCR, RPW, and KWC (Figure 5.7). To validate the digital model, all these methods were simulated. The output of this model matched the theoretical results and gave the same expected throughput (400 units) with almost the same line efficiency (76.34%). Individual workstation utilization shows workstation 2 (W2) is at near maximum efficiency and workstation 6 (W6) is least efficient (Table 5.5).

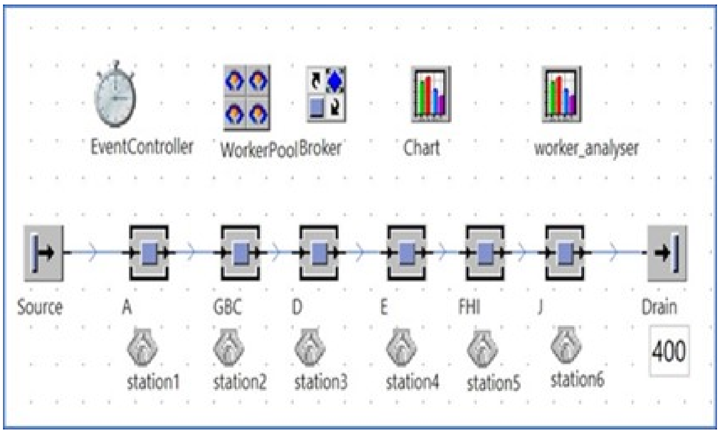

Figure 5.7: Tecnomatix 2D model for the assembly Line

Table 5.5: Workers' utilization for the heuristic‚Äôs methods using DES

Worker (W)	W1	W2	W3	W4	W5	W6	Total
Utilization	88.22%	99.74%	58.53%	87.67%	65.65%	58.22%	76.34%

Since all heuristics perform similarly, no matter which heuristic will be chosen for the simulation, KWC was entered into the simulation model as an initial solution and evaluated. After implementing DES, multiple improvement options have been raised. Simulation statistics showed that workstation 2 (tasks GBC) is the bottleneck, as it has the highest working percentage (highlighted with the red rectangle (Figure 5.8), resulting in blocking workstation 1 (task A) (Figure 5.8). As is common in live manufacturing, the bottleneck can move around the factory, and thus, dynamic adaptation to changing conditions is needed. DES was employed to simulate various scenarios through conducting “what-if" analyses to explore potential solutions for further improvement, such as:

1. Task reassignment
2. Reduce the number of workers
3. Reduce the number of workers with reassignment tasks

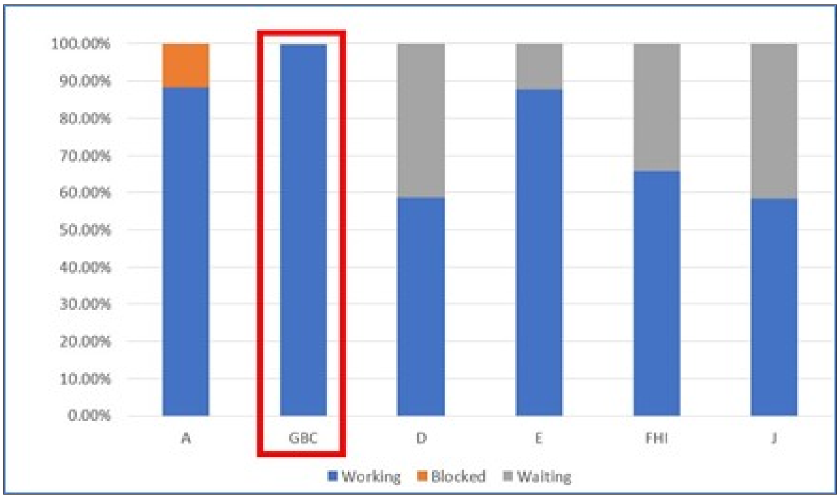

Figure 5.8: Stations' statistics for the heuristic methods using DES

5.4.2.2 Improvement scenarios using DES (phase 3)

DES provides a visual representation of the assembly line, enabling users to make adjustments and modify the system through what-if analysis. It also demonstrates the impact of these changes directly on the system's performance, including metrics like throughput and utilization. Leveraging the capabilities of DES, we formulated three improvement scenarios.

1. Task reassignment Following the heuristic assignment, the bottleneck workstation was workstation 2 because it blocked the first workstation so the first scenario for improvement is to reassign the tasks in a way that makes the processing time for workstation 2 less than the cycle time of 68 seconds. The suggested solution is grouping tasks G and B in the second workstation with a total processing time of 58 s and tasks C and D in the following workstation with a processing time of 50 s. This assignment removed the blockage from workstation 1 (Figure 5.9) and increased the production rate from 400 to 453 units without additional resources (same number of workers (6)) and the line efficiency increased up to 86.49% (Table 5.6).

Table 5.6: Workers' utilization for the first scenario using DES

Worker (W)	W1	W2	W3	W4	W5	W6	Total
Utilization	99.95%	96.42%	82.96%	99.30%	74.34%	65.95%	86.49%

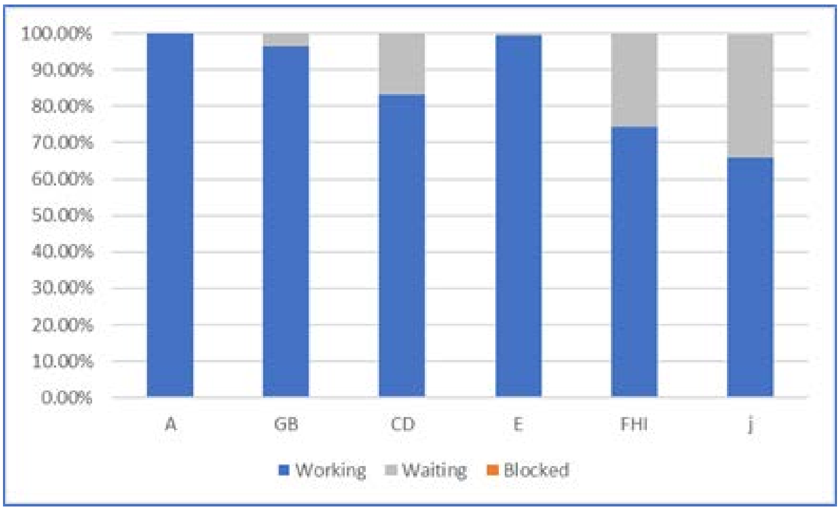

Figure 5.9: Stations' statistics for the first scenario

2. U-shaped layout Increasing the utilization of resources, such as workers, and eliminating idle time can enhance line efficiency. Waste time can be reduced by employing multi-skilled workers and optimizing facility layout. One possible solution is to switch the assembly line from a straight to a U-shaped layout, allowing workers to operate in multiple workstations with two directions, as illustrated in Figure 5.10.

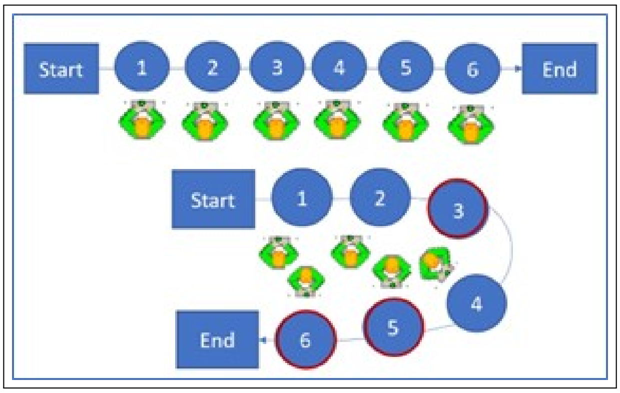

Figure 5.10: Straight and U-shaped assembly line

Before implementing this scenario, the workstations with lower utilization and higher idle time were workstations 6,3 and 5, respectively (Table 5). The U-shaped layout allowed workers to work on nonadjacent workstations, therefore reducing the number of workers to 5 instead of 6 and increasing the line efficiency to 91.59% (Table 5.7) while achieving the desired throughput (400 parts). Two workers instead of three are sufficient to handle the work on the workstations that have high idle time. In this scenario, the workers' travel time is assumed to be 1 meter per second, and they are permitted to leave their work and resume it later.

Table 5.7: Workers' utilization after the second scenario (U-shaped and deducting one worker)

Worker (W)	W1	W2	W3	W4	W5	Total
Utilization	88.22%	99.74%	91.27%	87.65%	91.06%	91.59%

3. Reduce the number of workers with reassignment tasks To develop a solution, we combined the first and second improvement scenarios. In this approach, tasks were assigned to stations based on the first scenario, and then the number of workers was reduced from six to five according to the second scenario. The reassignment of tasks proposed in the first scenario outperformed the theoretical assignments (LCR, RPW, KWC) when there were six workers. However, this scenario proved to be less effective when only five workers were present, resulting in a reduced throughput of 373 parts and a line efficiency of 85.64%, as presented in Table 5.8.

Table 5.8: Workers' utilization in the third scenario

Worker (W)	W1	W2	W3	W4	W5	Total
Utilization	82.57%	79.61%	81.92%	91.88%	92.24%	85.64%

The application of our approach resulted in multiple feasible improvement scenarios, each with a higher line efficiency compared to the heuristic method alone and compared to the current state of the observed facility. Table 5.9 compares the line efficiencies and throughputs for the existing case, theoretical methods, and the three proposed scenarios.

As illustrated in Table 5.9, the current state of the assembly line was not able to reach the required throughput. The line efficiency is computed by dividing the actual production rate(throughput) by the standard production rate time 100 % (255/350=72.8%), where 350 is computed by dividing the available time per day on the total task time to produce one enclosure (455 min/5.2 min = 87.5 enclosures/workers). So, four workers propose to produce 78.5*4= 350 enclosures. Analyzing the current state shows the assembly line suffers from two problems: first, shortage of resources (workers) and second, inefficient utilization of existing ones. By observing the line, we noticed that workers might be

Table 5.9: Comparison of existing and improved methods

State	Line efficiency	Throughput	Number of workers	Throughput per worker
Current state	72.8%	252	4	63
Theoretical methods	76.30%	400	6	66.6
Scenario 1	86.49%	453	6	75.5
Scenario 2	91.60%	400	5	80
Scenario 3	85.64%	373	5	74.6

assigned additional tasks beyond their designated roles, which reduces their efficiency within the line. The theoretical heuristics indicate the necessity of adding two additional workers to meet the desired demand and enhance efficiency to 76.3%. However, employing DES alone (scenario 1) yielded a 10% greater improvement in line efficiency compared to the theoretical solution. This was because DES was capable of identifying the bottleneck station, mitigating its impact by redistributing the workload, and transferring one task to the subsequent station. The second scenario was developed by integrating DES and heuristics, resulting in the highest efficiency of 91.6%. This achievement can be attributed to task assignments following heuristic principles, with DES optimizing the layout and reducing the workforce requirement. Conversely, the last scenario failed to match the throughput of five workers. This outcome was primarily due to DES driven task reassignment (as in scenario 1), and reducing the number of workers was not the optimal solution.

5.5 Conclusion

This paper introduced a new approach to solving assembly line balancing problems by using discrete event simulation combined with heuristic methods. The study aims to increase line efficiency and decrease the number of workstations and waste time, thereby enhancing the production rate. To assess the applicability of this new approach and compare it with existing methods, a case study was conducted at an enclosure factory located in Australia. First, the current state of the factory has been analyzed, and it was shown that the production line needs to be balanced to match the desired demand (400 units per day). The observed throughput was 252 units with line efficiency (72.8%). Three heuristic methods (LCR, RPW, KWC) were employed to enhance productivity, resulting in a consistent 76.4% efficiency across all techniques. While LCR and RPW exhibited similar task assignments, KWC differed. Despite these variances, overall performance remained the same. To further enhance efficiency, a DES model was developed, and based on it, several improvement scenarios were raised. The first scenario optimized task assignments, raising production to 453 units while eliminating the bottleneck workstation. The second scenario reduced workstations to five, achieving an impressive 91.6% efficiency. However, the last scenario fell short of meeting demand with five workers.

In conclusion, while the heuristics methods produced good results, they are static and not optimal. Our proposed approach, which integrates DES with heuristics, led to a significant improvement in line efficiency compared to using the heuristic method alone. While DES does not provide a guaranteed optimal solution, it effectively helps identify bottlenecks, accounts for stochasticity, explore various "what-if" scenarios, and determine better solutions. This approach is applicable to both small and large enterprises. As systems become more complex and incorporate additional entities, its performance may improve even further. However, with increased complexity, the computational cost of DES rises due to the greater number of events and interactions. GA can mitigate this issue by optimizing the simulation process, reducing the number of simulations needed to identify effective solutions, and thus lowering computational costs. This approach helps balance the need for detailed simulation with the practical constraints of computing resources. Additionally, it can be used on existing and non-existing production lines. In contrast to heuristic alone, it offers a visual representation of the process, enabling decision-makers to directly observe the impact of any modifications to their system's performance. Overall, the approach offers a promising solution for improving production line efficiency and reducing waste in a range of industrial settings. A limitation of this work is that the developed improvement scenarios are based on domain knowledge of the system and are not easily automated. It is assumed that workers could operate at full capacity all the time. While idealized these assumptions do not affect the core conclusions or the relative results of the case study. Additionally, this work considered SLBP to assemble one type of product, and only it tests three heuristics. A potential direction for future research is to apply this approach to GALBP, including a mixed model (various products assembled in the same line), investigate the combination of DES with metaheuristic methods, and a broader selection of heuristics.

CHAPTER 6

Cross-case analysis and discussion

This Chapter begins by addressing the research gaps, contributions, and research findings for each case study. It is followed by a cross-case analysis and then a detailed structure of the developed approach. Finally, a discussion will be provided comparing this thesis to the most relevant theses.

6.1 Research gaps, contributions, and the findings

This section summarises the research gap and contribution of each paper as well as their findings:

Paper 1 (Woolshed industry Production Planning)

Research gap: The wool industry has seen limited use of production simulations because of the absence of awareness in this field, including factors like farmers' age, attitude, and skills. Due to the industry's labor-intensive nature and the elevated risk of injuries, there is a conspicuous shortage of workers. This shortage underscores the urgent necessity to adopt automation in line with the progress of the fourth industrial revolution. Production simulations by providing visualizations and testing any changes to the shed design before implementing them can play a crucial role in offering clear insights into future planning, which is essential for the industry's evolution. This work covers the gap by applying discrete event simulation to evaluate woolshed design, which is a novel application in this industry.

Contribution: This work demonstrates that layout, resources, and processing time changes can significantly improve production in woolsheds and highlights the effectiveness of discrete event simulation in this context. It helps reduce the need for costly real-world experiments.

Finding: This research paper shows that DES can be employed to explore different improvement scenarios to increase daily throughput without disrupting the production process. These scenarios encompass modifying the facility layout, identifying bottleneck stations, determining the optimal speed for select stations to mitigate congestion, and assessing the effects of increasing resource availability. For instance, when applying the new approach to the wool industry. The results were as follows: Altering the shearing stand layout from a linear configuration to a curved one led to a 30% reduction in the wool handlers' traveling distance. Therefore, there was an 11-fleece-per-day increase in production. Introducing an additional skirting table in the curved layout further boosted production by 30 fleeces per day. However, there was no significant impact on production when it came to increasing the number of wool handlers. This work shows how improvements in this industry can be identified and evaluated using DES. According to Gittins et al. [95]. Their study reveals that attitudes toward computer simulation within the farming community were predominantly negative. Traditional farmers who resist technology serve as a significant barrier to its adoption. However, the research indicates that the younger generation of farmers is more receptive to this technology. This study represents one of the initial applications of discrete event simulation to assess woolshed operations and demonstrate its effectiveness in this domain. Through further simulation-based investigation of the wool harvesting process, an optimized production layout could be designed and examined with regard to its potential for improvement. This approach eliminates the need for costly planning, which is usually associated with high investment costs.

Paper 2 (Additive Manufacturing Production Planning)

Research gap: While much research in additive manufacturing focuses on part quality and printing technology, there's a gap in factory-level management and production planning using simulation. This gap can be attributed to the technology's predominant application in prototype construction and its relatively recent introduction to high-production settings, which has left this issue largely unexplored in the existing literature.

Contribution: The combination of discrete event simulation and genetic algorithms for production planning in additive manufacturing is a novel approach. The study provides insights into how to optimize scheduling and resource allocation in additive manufacturing facilities, which is essential for scaling up production.

Finding: In this research paper, the effectiveness of combining DES with genetic algorithms was investigated to reduce the total production time in the AM industry. DES was used first as an evaluation tool to analyze the performance of different resource configurations and to identify bottlenecks. Subsequently, GA was used to improve the makespan further by reordering the available jobs. For example, implementing the new simheuristic approach to multiple PBF factory sizes shows that its ability to identify the bottleneck station easily and adding extra workers could reduce the makespan by 30- 45% depending on the facility size. Adding extra resources at non-bottleneck stations could have no or little significant impact on overall performance. This shows the effectiveness of this hybrid approach as a production planning tool for dynamic production systems in additive manufacturing facilities that can help decision-makers determine the proper number of resources to deliver parts in time and how to allocate limited resources most efficiently and flexibly. Since this industry developed from producing prototypes to series production, This research is the second application after Wiese et al. [96], who considered AM process chain planning. The Majority of AM planning processes focus on the printing phase without considering the post-process. As the industry is evolving within the context of Industry 4.0, there is a growing need to pay greater attention to this specific field.

Paper 3 (Assembly Line Balancing Production Planning)

Research gap: Assembly line balancing is critical for maximizing throughput and reducing waste in manufacturing. In all assembly line balancing studies, simulation serves as the evaluation tool, either under the category of Simulation as an objective function or as an alternative solution to account for the stochastic nature of the system. This work covers the gap by integrating heuristic task allocation methods with DES to capture various factory settings.

Contribution: The study demonstrates that combining heuristic methods with DES can significantly enhance assembly line efficiency, surpassing the improvements achieved by each method separately. It offers a promising strategy for decision-makers seeking substantial enhancements in assembly line efficiency.

Finding: This study has shown the effectiveness of combining DES alongside heuristic methods in ALBPs, starting with the initial solutions obtained from heuristic, then entering this solution into the DES model and raising several improvement scenarios including layout changes, varying number of resources, and tasks rearrangement. Considering the stochastic nature of the studied system. The results gained from imple-

Table 6.1: Comparison of the three case studies

Study	Study 1: Wool industry	Study 2: AM industry	Study 3: Assembly industry
Industrial setting	Heavy manual LMHV	HMLV	LMHV
Implemented method	DES	DES+ metaheuristic (GA)	DES + heuristic (LCR, KWC, RPW)
Targeted Problems	Facility layout, bottleneck identification, resource planning	Scheduling, bottleneck identification, resource planning	Assembly line balancing, facility layout, bottleneck identification, resource planning
Objective (KPI)	Maximize throughput	Minimize makespan	Maximize throughput, and line efficiency
Productivity improvement	Curved layout showed better performance than the linear layout by an increase in output of 11 fleeces	Integrating GA into the DES model for scheduling introduced a further reduction in the makespan by up to 25%	Integrating heuristic with DES led to an increased line efficiency by 15 % more than using heuristic alone, and throughput per worker by 20%
Overall results	Improvements in this industry can be identified and evaluated using DES	Decision-makers could use this approach to determine the proper number of resources to deliver parts in time and how to allocate limited resources in the most efficient and flexible way in the HMLV environment	This industry could gain more benefit when using this approach by capturing the stochastic nature of the studied system

menting this approach in the enclosure assembly factory proved that. The throughput and resource utilization in this case study can be enhanced by an impressive 15% more compared to using heuristic methods in isolation.

6.2 Cross case analysis

Table 6.1 provides an overview of the three case studies, including aspects of the industrial settings, implementation method, type of the problem targeted, study's objective, achieved productivity improvement, and the overall results.

In summary, the simheuristic approach is suitable for three distinct industrial contexts: those characterized by significant manual involvement, scenarios involving a high mix with low volume, and situations with a low mix but high volume. Moreover, it has proven effective in catering to the needs of both small and medium enterprises, exemplified by its application in woolshed and additive manufacturing facilities, as well as larger enterprises, as demonstrated in the assembly line study. The structure of this approach is detailed in Section 6.3.

6.3 The proposed approach context

The approach developed through this thesis outlines several steps and serves as a road map for production planners and decision-makers. It encompasses general processes, simulation modeling processes, and optimization processes (Figure 6.1). The color coding in this figure highlights the high-level steps. A detailed explanation of each step is provided in the text below.

6.3.1 General processes

First, The general processes with blue code (Figure 6.1) represent the systematic approach applicable to problem-solving in any context. Nevertheless, this approach is specifically tailored based on the studied cases, incorporating three essential steps as outlined below:

1. **Problem definition:** In order to address any problem effectively, the initial step is to clearly define it. This encompasses various challenges, including facility layout problems, flow shop scheduling problems, assembly line balancing problems, resource allocation problems, and scheduling problems. Additionally, it involves the identification of bottlenecks within the system.

    - **Facility layout problem** (FLP) is concerned with arranging equipment, workstations, machines, and departments in a way that achieves a desired objective for existing or new facilities. A layout decision is primarily concerned with ensuring a smooth flow of information, people, material, and work [97]. For example, in the wool industry study, two different layouts of the woolshed have been evaluated.

- **Flow Shop Scheduling Problem** (FSP), This type is a common production problem where a group of jobs have to be carried out on a set of machines with similar workflows. The goal is finding the optimal or near-optimal assignments that maximize or minimize a particular objective (e.g., Makespan, lateness, Tardiness) [98].
- **Assembly Line Balancing Problem** (ALBP), this type is classified as a decision-making problem, where the tasks have to be distributed among the workstations equally to optimize some performance measures such as increasing the production rate, the line efficiency and reducing the overall idle time [99].
- **Resource planning problem:** It involves assessing the number of workers, machines, and materials required to execute project activities [100].
- **Bottleneck identification**: The act of recognizing a particular step within a series of processes that acts as a limiting factor due to its restricted capacity, consequently constraining the overall capacity of the entire process chain [101].

2. **Objective determination**: To assess the productivity improvement of a production system, it is essential to identify key performance indicators (KPI) depending on the objective. That could be either minimizing or maximizing some performance indicators such as:

   - **Throughput**: It measures the actual output of products or services.
   - **Resource utilization and efficiency:** It measures how effectively and efficiently resources, such as workers, machines, or materials, are used within a system.
   - **Makespan:** total production time to complete a set of tasks or jobs in a production process.

3. **Data collection**: This process includes collecting data from several sources, such as direct observations, motion and time studies, literature studies, and interviews. The nature of data can be classified as workstation processing time, workstation layout, Process sequence, and number of available resources.

6.3.2 DES processes

After incorporating the fundamental general processes, the subsequent DES processes are executed (highlighted with green in Figure 6.1). These processes encompass the following steps:

4. **Model construction:** building a digital model mimics the physical system using one of DES software. Some well-known suitable commercial software: Arena by Rockwell Automation [102], FlexSim by FlexSim Software Products [103], Plant simulation by Siemens [104], and Witness by Lanner [105]. Any of these software can be employed to solve various types of problems. However, the selection depends on the preferable programming environment, toolboxes, or add-in functions. In the thesis, Tecnomatix Plant Simulation was employed to construct the model. It incorporates the Simtalk programming language for implementing customized behaviors and logic in the simulation model, addressing aspects not covered by the built-in functionality of the simulation. See Appendix D for the code that has been used to build and control the simulation model that represents the production flow in the woolshed (Chapter 3).

5. **Model verification and validation:** Verification is verifying that the digital model has been built correctly. Validation is determining if the built model accurately represents the real-world system. In the three studies, the models underwent thorough verification and validation before being employed in subsequent analyses to ensure that their outputs align with the actual outputs of the physical system.

6. **Model analyzing:** This stage examines the current system's behavior to identify its weaknesses. A what-if analysis is conducted to generate and assess various improvement scenarios, evaluating their potential impact on production outcomes. This analysis encompasses simulating alterations in production volumes, introducing new resources, modifying production lines, or testing alternative production strategies. Decision makers can analyze the results of these simulations to assess different options to enhance the efficiency and productivity in their facility [106]. Various improvement scenarios were raised in the three studies in accordance with the decision-maker's vision.

6.3.3 Optimization processes

The commencement of this procedure occurs after the acquisition of study data. The integration of heuristic techniques and Discrete Event Simulation (DES) encompasses the subsequent steps:

7. **Heuristic selection:** This phase involves choosing the most appropriate heuristic that best fits the problem from a range of available heuristics.

8. **Heuristic implementation:** This stage provides theoretical solutions for the problem. As heuristics represent strategies for problem-solving, there isn't a dedicated computational tool or software for their implementation. They can be applied manually or through Microsoft Excel and programming languages like Python, Java, etc.

9. **Heuristic evaluation:** In this step, the performance of the chosen heuristic is assessed by comparing it to other available options.

   The final step is to integrate both techniques together following simulation optimization class 2 (simulation as objective function), and class 3 (simulation results as a start for optimization) to obtain an optimized solution:

10. **Heuristic integration**: This phase integrates the heuristic solutions to the simulation model and evaluates it. Then, an iterative optimization process could be applied until a satisfactory solution is obtained. In the case where the solution remains unsatisfactory, various scenarios can be explored. This exploration may involve adjusting factors such as resource allocation or implementing scheduling modifications. The genetic algorithm could be used to assign jobs to workstations effectively.

Finally, the whole approach is summarised in Figure 6.1, which represents the final structure of this approach.

6.3.4 Comparison to the most relevant thesis:

The thesis by Gerdin [7] highlights the importance of using simulation modeling to enhance manufacturing systems, emphasizing the potential benefits for industrial plants. However, it also acknowledges challenges in applying simulation in practice, mainly related to **social and organizational acceptance**. The thesis suggests that simulation

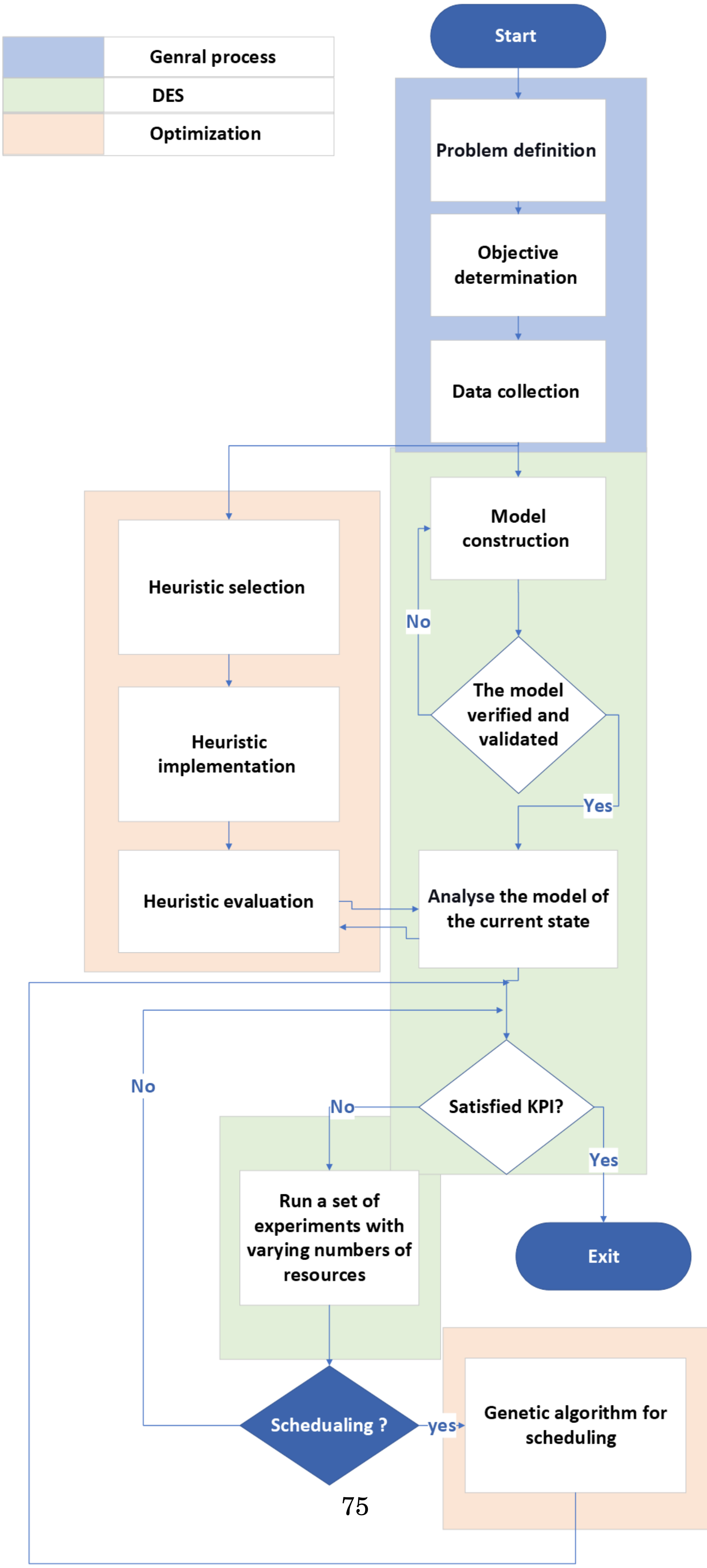

Figure 6.1: The proposed Simheuristic approach

can complement other plant objectives and proposes **future work involving model optimization and real-world implementation** to validate its effectiveness in providing an accurate representation of system behavior. As an extension of this research, the new simheuristic approach has been applied in industries that are traditionally resistant to simulation adoption, such as the wool industry case. This application demonstrated the benefits of simulation in designing wool sheds and improving productivity. This case can serve as a motivating example for other agriculture sectors that heavily rely on manual labor and have yet to embrace technological advancements. Furthermore, the new simheuristic approach incorporated optimization methods into the developed simulation model, exemplified in the additive manufacturing and assembly line balancing case studies demonstrating the application and efficacy of optimization techniques within the simulation framework.

In Lathher's thesis [21], Lather introduced a framework that integrates simulation, optimization, and visualization for healthcare facility layout planning to optimize the process and layout. The findings show that this integration helps in assessing five different layouts efficiently. Similarly, the research carried out by Asio [107] conducted a DES model to create a facility layout plan for a grain delivery terminal; her research aims to identify bottlenecks and optimize the number of resources to minimize the average waiting time. This thesis findings align with the previous study ([21]) and ([107]) on the effectiveness of DES in evaluating various facility layouts and its impact on the performance of production as illustrated in the first study (Chapter 3) in evaluating two different layouts of the studied wool shed. However, the proposed approach extends beyond facility layout concerns. It encompasses a comprehensive framework that can be applied to various problems such as scheduling problems, resource planning problems, and bottleneck identification as presented in Chapter 4, assembly line balancing problem as illustrated in the third study (Chapter 5). This thesis provides a systematic method for researchers to consider when utilizing simulation in their work and shedding light on various problems that can be taken into account at the production planning level.

Chapter 7

Conclusion

This section presents a summary of this thesis, contributions to knowledge, practical implications, research limitations, and potential avenues for future research.

7.1 Summary

These days, production enterprises are evolving to become more dynamic and complex due to advances in technology that have arisen from the fourth industrial revolution. Factors such as short product life cycles, demand fluctuation, and a more complex network of the production flow raise the need for advanced production planning tools through forecasting, assessing, and comparing the efficiency of physical facilities and manufacturing. Integrating simulation into the production planning process is crucial for these enterprises to anticipate and project their performance accurately. The primary objective of this thesis is to pioneer a novel approach in the production planning process, specifically designed to assist decision-makers in enhancing the productivity of their production systems. This approach aims to be comprehensive, offering a thorough analysis of various improvement scenarios. To achieve this goal, three distinct production areas were examined: heavily manual processes with low mix high volume, high mix low volume, and low mix high volume. The findings indicate that the proposed approach exhibits efficacy across these diverse production areas. For instance, in the woodshed industry, DES successfully applied to address challenges such as the facility layout problem and resource planning. This thesis demonstrates how different improvement scenarios can be systematically examined, highlighting their respective impacts on total throughput. In additive manufacturing, scheduling problems and resource allocation problems have been addressed, and the effectiveness of integrating DES and genetic algorithms in reducing the total production time was highlighted. The advantages of this integration were particularly notable as the factory scaled up. The last study, in assembly line balancing, showed that low mix high volume industry could benefit from this approach, implementing the new approach to balance the workload on the workstations. The throughput and resource utilization in this case study were enhanced by an impressive 15% more compared to using heuristic methods in isolation.

7.2 Academic Contribution

This thesis contributes to the existing body of knowledge in the field of manufacturing and operations management. The methodology serves as a theoretical advancement, offering a framework that can guide and inform similar production systems.
The developed approach, which is built upon the integration of discrete event simulation with heuristic optimization, offers a range of significant advantages:

Flexibility: This approach demonstrates a remarkable capability to compare alternatives, evaluate trade-offs, and incorporate elements such as randomness, variability, dependencies, feedback, and interactions among various components within a system.

Stochastic and Dynamic Characteristics: Unlike alternative methods, the combination of DES and heuristic optimization excels in capturing the stochastic and dynamic behaviors of systems, providing insights that may remain elusive through other approaches.

Comprehensive Solutions: The approach proves invaluable in addressing a spectrum of industrial challenges, including bottleneck identification, scheduling, facility layout design, and resource allocation.

Enhanced Decision-Making: Beyond mere analysis, the fast and optimized solutions generated by this approach empower decision-makers to identify the most optimal course of action efficiently.

Applicability Across Settings: The versatility of this approach extends to various settings, making it a robust and adaptable tool for decision support in diverse industrial contexts.

7.3 Practical Implication

The proposed methodology aims to enhance the productivity and service levels of comparable manufacturing systems. Furthermore, it can function as a guiding framework for similar production systems. The consequential improvement in productivity and service levels offers manufacturing companies with aging facilities a competitive edge against newly established factories. The outcomes can furnish valuable insights for managers, stakeholders, and decision-makers, assisting them in making informed decisions and facilitating the implementation of transformation changes and redesigns in their manufacturing systems.
Planning and managing industrial processes should prioritize critical elements, including **optimizing resource allocation, tasks allocation, designing effective facility layouts, efficiently scheduling operations, and identifying bottlenecks**. The integration of all these elements into a digital simulation model, which emulates real-world scenarios and incorporates heuristic optimization techniques, empowers industrial decision-makers with a more comprehensive understanding, enhanced control, and the ability to optimize their production processes. The proposed approach not only addresses a multitude of industrial challenges but also demonstrates adaptability in handling the complexity and dynamism of the systems under study, thereby facilitating the decision-making process.

In summary, these three case studies address specific gaps in research within their respective domains by introducing novel approaches or methodologies and providing practical insights into improving production processes, whether in woolsheds, additive manufacturing, or assembly line balancing. **However, various industries beyond those could benefit from this approach, such as automotive manufacturing, healthcare, supply chain management, aerospace, etc.** That may fall under the same categories, such as high-mix, low-volume, and low-mix high-volume production. All cases considered the stochastic nature of workstations' processing time, failure, and shift time, which capture the stochasticity and dynamic of the system in contrast to the traditional method, as well as the ability to group several problems and solve them at one time.

7.4 Research limitations

Here are some potential challenges and constraints associated with this approach:

- Despite the numerous benefits that could be derived from this approach, conducting a cost analysis is crucial. Simulation is not without expenses, and factors such as the cost of simulation software licenses and the time invested in developing the model need to be evaluated compared to other planning methods.
- There is no guarantee that this approach would prove effective in another setting, and it may or may not be suitable for scenarios entirely different from those observed in the specific case studies, such as low mix low volume situations, because there is not a significant production flow to analyze, and the problem becomes less intricate. Similarly, in high mix, high volume settings, which represent a newly developed setting, the applicability of the approach remains uncertain. However, this thesis shows the applicability of this approach in diverse settings; this indicates a high likeliness for broader applicability in other settings.
- Several assumptions were made during the development of the simulation model due to the difficulty of fully capturing the real system during the simulation. For example, in the wool industry study, worker parameters were assumed to be constant for both layouts (chapter 3). In additive manufacturing study (chapter 4), Setup time is considered as a part of the processing time.
- The current integration has primarily focused on genetic algorithms and assembly line balancing heuristics. The limitations of these methods may overlook potential benefits that could be gained from other optimization algorithms. Exploring a broader range of optimization techniques could reveal more effective approaches for specific scenarios.
- Optimization is a crucial aspect. However, the integration may not fully address the cost implications of improvement scenarios. A more comprehensive analysis that considers various cost factors and their impact on the optimization results could provide a more realistic assessment of the proposed changes.
- Data were collected manually based on observation or from literature.

7.5 Future Work

This thesis explores the significant advantages of digitalization across various industries, including those still in their early stages, such as the wool industry. Digitalization enhances our understanding of production systems and allows for adjustments without disrupting operations. As companies expand and the connections between their components grow more complex, tracking these connections becomes increasingly challenging. Digitalization offers a viable solution to managing this complexity, potentially serving as a key component in navigating the complexities of the Fourth Industrial Revolution (Industry 4.0).

Industry 4.0 envisions utilizing real-time data and analytics within manufacturing and industrial environments [21]. Integrating real-time data into the built simulation model, such as implementing sensors and cameras that capture the processing time, failures could have a huge benefit and reduce the efforts of collecting these data by observation and end with a more accurate model. Integrate other optimization algorithms and compare their performance. Increase the complexity of the studied system by incorporating multiple assembly lines featuring diverse assembly line types, including mixed model assembly lines and introducing additional problems to this approach, such as buffer allocation problems, energy consumption analysis to promote sustainability, and cost analysis for the improvement scenarios.

APPENDIX A

APPENDIX

Table A.1 shows the results from running the model five times (replicant) on the number of sheared fleeces under the curve layout scenario as the number of wool handlers was varied.

Followed by the SimTalk programming codes that were used to control the production flow in the woolshed case study.

Table A.1: Number of sheared fleeces for each replicate under the curve layout scenario

Number of wool handlers	Replicant 1	Replicant 2	Replicant 3	Replicant 4	Replicant 5
2	826	826	826	826	826
3	827	827	827	827	827
4	828	828	828	828	828
5	833	833	833	833	833
6	833	833	833	833	833

```
--Counting number of bales in each store
var MuCount:integer;


if Store1.numMU > 0
    A_Value := Store1.numMU*.MUs.Container.zDim ;
end

if Store2.numMU > 0
    B_Value :=
Store2.numMU*.MUs.Container1.zDim*.MUs.Container1.xDim*.MUs.Co
ntainer1.yDim;
end

B :=
(Buffer1.numMU+Buffer2.numMU+Buffer3.numMU+Buffer4.numMU+Buffe
r5.numMU)/36
--------------------------------------------------------------
--Open and close the bag source

if skirtingTable.numMu > 0 then

    end;

if Buffer.numMu > 0 then

end;

if Pressing11.numMu >0
    Bag_Source.blocking := true
    Bag_Source.Exitlocked:=true

else
    Bag_Source.blocking:=false
    Bag_Source.Exitlocked:= false

end

if Pressing21.numMu >0
    Bag_Source1.blocking := true
    Bag_Source1.Exitlocked:=true

else
    Bag_Source1.blocking:=false
    Bag_Source1.Exitlocked:= false

end
```

```
-- Carrying and inserting the bag in the presser
if Pressing11.numMu =0 then
        Bag_Source.ExitStrategy := "Carry Part Away";
        Bag_Source.TransportImp.BrokerPath := Broker1;
        Bag_Source.Mutarget := Pressing11;
end;

if Pressing21.numMu =0 then
        Bag_Source1.ExitStrategy := "Carry Part Away";
        Bag_Source1.TransportImp.BrokerPath := Broker1;
        Bag_Source1.Mutarget := Pressing21;
end;

--------------------------------------------------------------

if  pressing21.NumMu > 0 then
        variable := pressing21.Cont.numMU
    end;


-----skirting table Workers-------

    var services:table[string,integer,string]
    var number:integer
    services.create
if skirtingtable.empty then
if  Buffer_Skirting.Buffer_Sk_MuName = "A" and
.UserObjects.classifier.empty  then
    --SkirtingTable_WP2.station := "SkirtingTable"
    services[1,1]:="skirter"
    services[2,1]:=2
    services[1,2]:="classifier"
    services[2,2]:=1
    Skirtingtable.imp.setServices(services)
    --Skirtingtable.procTime := 30
else
    --SkirtingTable_WP2.station := "Buffer"
    services[1,1]:="skirter"
    services[2,1]:=2
    Skirtingtable.imp.setServices(services)
    --Skirtingtable.procTime := 45
end;
end;
```

```
---------------------Pressing 1 Recovery Time-------------------

if SkirtingTable.statNumIn = 0 then
    Press1_RecTime := 180
end;


if pressing11.numMU > 0 then
if pressing11.Cont.numMU >35 then
    Pressing1.EntranceLocked :=true
    Pressing11.EntranceLocked :=true
end;
end;

if Pressing1.EntranceLocked and Not Press1_RecTime_Dn then
    Press1_RecTime_Dn := True
end;

if Pressing1.EntranceLocked and Press1_RecTime_Dn then
    Press1_RecTime:=z_uniform(10,120,150)
    --Press1_RecTime:= 150
    &Pressing1_Meth.methcall(Press1_RecTime) -- call the
method in 2 mins & 30 secs
end;

-------------Sorting the fleece according to their type-------

var Wool_Type := skirtingTable.Mu.Name
    switch Wool_Type
    case "A"
            skirtingTable.MainMU := 1;

    case "B"
        skirtingTable.MainMU := 2;

    case "C"
                skirtingTable.MainMU := 3;
    case "D"
        skirtingTable.MainMU := 3;
    case "E"
                skirtingTable.MainMU := 3;
    case "F"
                skirtingTable.MainMU := 3;
    case "G"
        skirtingTable.MainMU := 3;
    end;
```

```
-----Sorting the fleece according to their type, continue ----

var Wool_Type_Buffer := Buffer.Mu.Name
    switch Wool_Type_Buffer

    case "C"
        Buffer.ExitStrategy := "Carry Part Away";
        --Buffer.TransportImp.BrokerPath := Broker1;
        Buffer.Mutarget := Buffer1;

    case "D"
        Buffer.ExitStrategy := "Carry Part Away";
        --Buffer.TransportImp.BrokerPath := Broker1;
        Buffer.Mutarget := Buffer2;

    case "E"
        Buffer.ExitStrategy := "Carry Part Away";
        --Buffer.TransportImp.BrokerPath := Broker1;
        Buffer.Mutarget := Buffer3;

    case "F"
        Buffer.ExitStrategy := "Carry Part Away";
        --Buffer.TransportImp.BrokerPath := Broker1;
        Buffer.Mutarget := Buffer4;

    case "G"
        Buffer.ExitStrategy := "Carry Part Away";
        --Buffer.TransportImp.BrokerPath := Broker1;
        Buffer.Mutarget := Buffer5;

    end;
```

Appendix B

APPENDIX

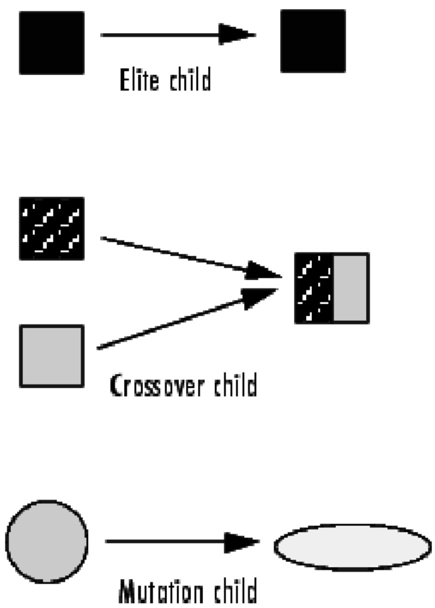

Figure B.1: Types of children after crossover and mutation [4]

APPENDIX C

APPENDIX

Figure C.1 shows a screenshot of the parameters used to set up the GA wizard in Tecnomatix plant simulation

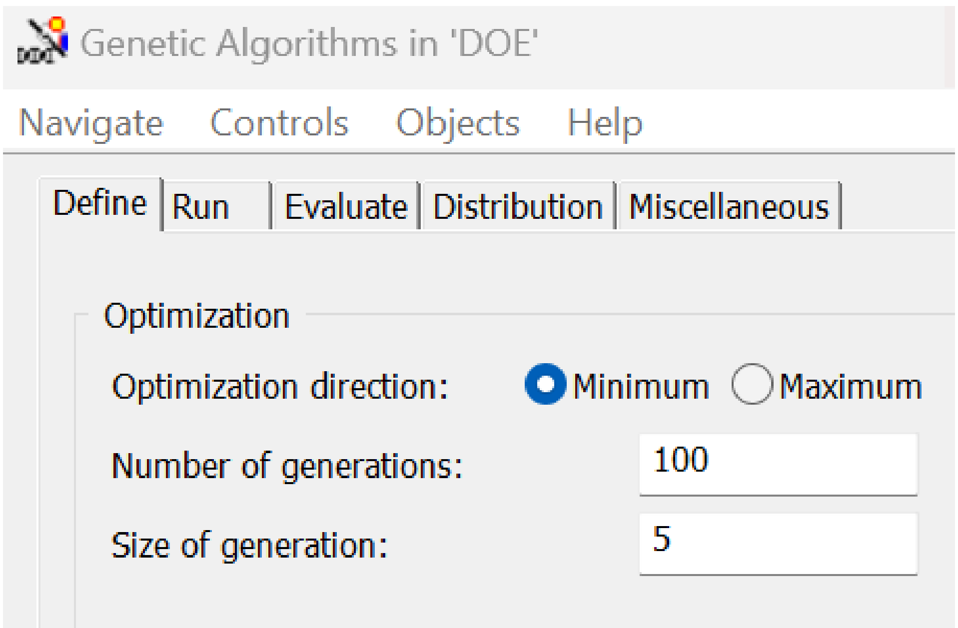

Figure C.1: GA's parameters

Appendix D

Appendix

This appendix presents the makespan values from 5 replications (Rep) of the DES model runs. Table D.1 and Table D.3 display the makespan in the format of days: hours: minutes: seconds, before and after implementing the GA, respectively. Table D.2 and Table D.4 provide the same data converted into seconds, along with additional statistical information, including the mean and standard deviation.

Table D.1: Makespan values for five replications (Rep)

	Makespan (dd:hh:mm:ss)				
EXP (1)	Rep 1	Rep 2	Rep 3	Rep 4	Rep 5
1	19:02:25:35	19:02:26:00	19:02:24:55	19:02:25:40	19:02:25:26
2	19:02:25:35	19:02:26:05	19:02:24:55	19:02:25:45	19:02:24:45
3	13:07:32:55	13:07:33:00	13:07:33:20	13:07:32:45	13:07:33:10
4	13:05:33:20	13:05:33:45	13:05:33:30	13:05:32:55	13:05:34:10
5	12:02:44:30	12:03:44:45	12:02:44:35	12:02:25:20	12:02:44:50
6	12:01:29:55	12:01:30:10	12:01:30:30	12:01:30:05	12:01:30:25
7	13:07:30:05	13:07:30:15	13:07:30:30	13:07:29:50	13:07:30:25
8	12:02:12:50	12:02:14:10	12:01:13:30	12:02:13:45	12:02:12:50
9	12:02:05:45	12:02:05:50	12:02:05:30	12:02:05:55	12:02:05:40
10	12:01:29:50	12:01:31:10	12:01:30:15	12:01:32:20	12:01:28:45

Table D.2: Makespan values for five replications (Rep), where the units converted to seconds

	Makespan (seconds)						
EXP (1)	Rep 1	Rep 2	Rep 3	Rep 4	Rep 5	Mean	S. d
1	1650335	1650360	1650295	1650340	1650326	1650331.2	23.76
2	1650335	1650365	1650295	1650345	1650285	1650325	33.91
3	1150375	1150380	1150400	1150365	1150390	1150382	13.50
4	1143200	1143225	1143175	1143210	1143250	1143212	27.97
5	1046670	1046685	1046675	1046665	1046690	1046677	10.36
6	1042195	1042210	1042230	1042205	1042225	1042213	14.40
7	1150205	1150215	1150230	1150190	1150225	1150213	16.04
8	1044795	1044770	1044860	1044810	1044750	1044797	42.07
9	1044345	1044350	1044330	1044355	1044340	1044344	9.61
10	1042190	1042270	1042215	1042320	1042125	1042224	74.78

Table D.3: Makespan values for five replications (Rep) with implementing GA

	Makespan (dd:hh:mm:ss) with GA				
EXP (1)	Rep 1	Rep 2	Rep 3	Rep 4	Rep 5
1	16:05:50:30	16:05:50:25	16:05:50:20	16:05:30:25	16:05:50:25
2	16:05:50:00	16:05:50:20	16:05:50:50	16:05:50:55	16:05:51:01
3	12:02:37:00	12:02:36:45	12:02:38:15	12:02:37:30	12:02:36:10
4	12:02:41:59	12:02:42:00	12:02:42:00	12:02:42:02	12:02:42:01
5	9:03:31:40	9:03:31:50	9:03:31:30	9:03:31:45	9:03:32:00
6	9:02:57:45	9:02:59:10	9:02:58:25	9:02:58:35	9:02:58:30
7	12:02:37:35	12:02:37:25	12:02:37:45	12:02:37:30	12:02:37:50
8	9:01:35:55	9:01:36:15	9:01:36:05	9:01:36:10	9:01:37:00
9	9:01:29:40	9:01:29:55	9:01:29:50	9:01:30:00	9:01:29:45
10	9:01:10:35	9:01:10:55	9:01:10:42	9:01:10:43	9:01:10:55

Table D.4: Makespan values for five replications (Rep) with implementing GA, where the units converted to seconds

	Makespan (seconds) with GA						
EXP (1)	Rep 1	Rep 2	Rep 3	Rep 4	Rep 5	Mean	S. d
1	1403430	1403425	1403420	1403430	1403425	1403426	4.18
2	1403400	1403420	1403450	1403455	1403461	1403437.2	26.10
3	1046220	1046205	1046295	1046250	1046170	1046228	47.24
4	1046460	1046520	1046520	1046522	1046521	1046508.6	27.18
5	790260	790310	790290	790305	790320	790297	23.34
6	788220	788350	788305	788315	788310	788300	48.08
7	1046220	1046245	1046265	1046250	1046270	1046250	19.68
8	783300	783375	783365	783370	783420	783366	42.92
9	782940	782995	782990	783000	782985	782982	24.13
10	781835	781855	781842	781843	781855	781846	8.774

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