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A Simulation-based Optimization Approach for Automated Vehicle Scheduling at Production Lines

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Abstract

The world becomes more integrated and sophisticated, especially in the birth of advanced technologies, which have influenced all life aspects. Automated systems could be considered an example of those aspects, which have been affected by recent changes in today's life. The competition in the market is putting increasing pressure on different manufacturing organizations to find the best methods that enable them to stay up to date with the latest technologies in the industrial field. One of the most famous dilemmas that exist in this field is designing an efficient and flexible material handling system. This issue draws the attention of both decision-makers in different companies and software developers who put considerable effort into making that desired system real. Inclusive research needs to be performed to obtain such a system, and the most significant part of the research that requires special attention is the applied methodology.

The approach to be adapted determines the degree of stability of a particular material handling system to function effectively in the case studied. Several methods are available and could be implemented to design that effective system such as meta-heuristic algorithms, and approaches that depend on simulation software tools. The latter approach, which is the simulation approach, seems to get increasing attention from developers of the industrial system since it plays a vital role in reducing the cost and preserving available resources. Besides, it helps predict future changes and scenarios of the system to be analyzed.

In this project, a discrete-event simulation model was built for the proposed layout of the main shop floor owned by a Swedish manufacturing company. The corporation located in the south of Sweden, and it produces a vast range of manufacture of goods. The chosen methodology is a combination of lean, simulation, and optimization approaches. It has been implemented on the proposed layout in which material is handled into production lines by using automated guided vehicles (AGVs) as a means of transportation. The analysis of results shows potential benefits, where the production process became more efficient and organized since the operational cost has been reduced by decreasing the number of required vehicles. Moreover, the simulation approach facilitated testing new ideas and designing improved scenarios without the necessity to change the current state of the factory layout or disturbing the regular activities.

Keywords: Discrete-Event Simulation, Material handling system, Lean and Simulation-based Optimization, Vehicles scheduling.

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Skövde, August 2019

Osama Marwan Altrabulsy

Certificate of Authenticity

Submitted by Osama Marwan Altrabulsy to the University of Skövde as a Master's Degree Thesis in "Industrial Systems Engineering" at the School of Engineering Science.

I certify that all material in this Master Thesis, which is not my work, has been adequately referenced.

Skövde, August 2019

Osama Marwan Altrabulsy

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1 Introduction

Effective manufacturing systems are characterized by high flexibility and fast response to keep in touch with the advances in living standards. Hence the flexible manufacturing systems are unavoidable in terms of developing the production process and the end-users' satisfaction. Besides, these systems increase machine utilization and productivity of production lines. This productivity is affected by many factors, which influence the efficiency of the whole system, like the operational expenses. Besides, ineffective vehicle scheduling and routing can cause a considerable quantity of resources waste and, therefore, a high operational expenditure (Lin et al., 2017).

This issue drew great attention in the last decades because of its significance in the manufacturing systems design. The vehicle scheduling problem concerns assigning vehicles to a predetermined set of timetabled trips while satisfying some requirements, such as the number of depots that should be visited on each trip. The best schedule is characterized by the minimum number of vehicles used, and this helps in turn in decreasing the operational cost. Moreover, the type of vehicles available before each round should be identified based on the delivered materials to the assembly lines. In this case study, the material can be delivered to the lines in kits in the form of pallets or plastic boxes. Different material handling equipment can be used for this purpose, such as forklifts, tugged trains, or automated guided vehicles (AGV). However, AGV was selected to be the material handling equipment for this study.

The aim of this project is, going through a case study in an industrial company to design an effective material handling system on the company's main shop floor and indicate the optimal number of vehicles that responsible for delivering different necessary parts into assembly lines. The background, problem description, aim and objectives, and limitations of this project are explained in the following sections.

1.1 Background

Vehicle routing problem (VRP) refers to a class of combinatorial optimization problem which seeks to find the optimal routes of a set of vehicles in order to improve the whole logistics system. This involves either the flow of products from manufacturing plants through the transportation network to consumers or the inner flow in the manufacturing plants throughout different production areas (Torres et al., 2015). The vehicle scheduling problem refers to assigning vehicles to a predetermined set of timetabled trips following the optimal route that fulfills the minimal operation cost. Thus, the problem of vehicle scheduling and routing plays an intrinsic role in the process of designing an effective material handling system (MHS) (Haksever et al., 2000). Another critical factor that affects MHS design is the lead time (LT) that is considered one of the most significant factors, and it affects the whole production process because the longer the lead time is, the lower the productivity would be.

It is so evident that the throughput says how much a company earns, and the lead time influences it, so it is significant to consider it. The lead time is mostly affected by an important factor which is the material handling system, and if this system is organized poorly, it will cause several problems such as unwanted movements that do not add value to the work, long waiting time that will delay the whole process as well as unorganized shop floor in general. A robust material handling system can lead to lower the company's operating costs significantly, and it has numerous positive effects on the whole manufacturing system. Drira et al. (2007) stated that a good design of a material handling system could decrease the cost by 10-30 percent. Thus, it is a requirement to design an efficient material handling system during the expansion or adaption process or even under the construction phase.

1.2 Problem description

This study will highlight the need for designing a robust material handling system in the manufacturing plant of this study. The current shop floor of the manufacturing company produces a wide range of product types. The materials are delivered to assembly lines, and they are stored close to them in line-side buffers. The company uses forklifts for the material delivery except for the last line, where they use AGV, and the transported materials are stored in specific boxes located inside some pallets. In the main shop floor, the company produces commodities in two different ranges; small-range having four dedicated lines, and mid-range that are produced on the other four lines.

However, the current material delivery process is not efficient as expected because it causes considerable waste in transportation since materials are usually located in different stores. Therefore, operators at assembly lines should spend some time to gather all the necessary parts to form a particular product. On the other hand, in the push system, materials are delivered continuously. This kind of material delivery leads to waste in transportation because the vehicle will transport materials even if they are not needed at assembly lines. Moreover, the case study company assigns separated line-side buffers for each line with higher capacities than required, and this demands larger spaces to keep boxes and results in a high level of inventory. Thus, all mentioned wastes result in increasing lead time and causing an inefficient production process.

As stated above, the company's shop floor is not as efficient as it should be, and this causes waste in the material delivery process. For all the reasons mentioned above, it is essential to find solutions to the current state situation. This thesis tackles this issue and introduces a new arrangement of the shop floor. Besides that, a new material handling system that adapts the kitting feeding policy also is considered. Then the number of required transporters is minimized to the lowest value that still can deliver the daily demand. **Figure1**, presents the proposed layout of the main shop floor. All measured distances are in meters.

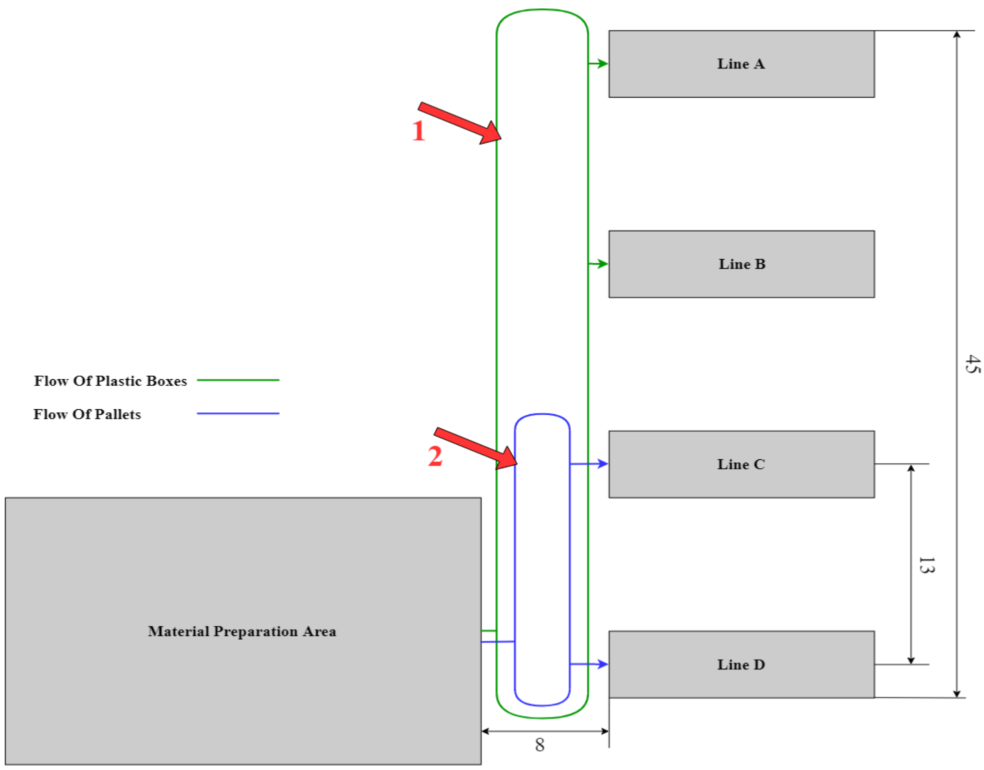


Figure 1. The proposed layout of the main shop floor

As shown in the previous figure, the concept of the supermarket or material preparation area (MPA) was implemented. The paths that vehicles follow are also shown; the first route (green color) is for vehicles that deliver parts for small-range products, and the second route (blue color) is used to deliver parts for mid-range products. The assembly area consists of four production lines, line A and line B are devoted to producing goods of small-range whereas, line C and line D are for goods of mid-range.

1.3 Thesis objectives

The main objective of this thesis is to design a new material handling system for the proposed layout (Figure1) of the main shop floor for the factory through:

- Building a conceptual model of the proposed layout of the main shop floor.
- Building the simulation model of the proposed layout of the main shop floor, including the material supply system using one of a simulation software like Facts analyzer, then analyze the system and design possible what-if scenarios.
- Validate the simulation model with the company representative to have a decision later if it is suitable and valid externally and internally to implement it in the factory.
- Optimize the simulation model in Facts analyzer, for instance, by indicating the decision variables that affect the outcomes of the whole model.

Moreover, some other objectives of the optimization process are handled in this project like to minimize the required number of vehicles, decrease the capacities of line-side buffers and part buffers, reduce the length of conveyors, decrease the value of lead time and WIP.

1.4 Limitations

Discrete-event simulation (DES) is a stochastic and dynamic method that has random input variables, and the outputs are random as well. In other words, discrete event simulation is "the modeling of a system in which the state variables change only at a discrete set of points in time" (Banks et al.,2005). Thus, it is essential when applying this simulation approach to know when to stop modeling. The challenge is to realize how deep the details of a model should be to have supportive findings. This issue requires to have a set of assumptions during data collection and modeling processes of the system (Chung, 2003). A list of assumptions is defined to show the different suppositions about the collected data at the early stages of the project. Besides, during the model development. These assumptions are necessary to be considered to facilitate and simplify the comprehension of the conceptual model and the simulation model. It is essential to mention that the project is delimited to the internal logistics of the main shop floor, more specifically, to the material feeding of the lines. Appendix-1 shows a table containing the list of this study assumptions; for example, there is just one supermarket serving the four assembly lines. This means that all AGVs are going to visit it during each process of loading and unloading parts that form different products. Another assumption, for example, states that the traveling AGVs follow predetermined paths, meaning that the distances and time of each cycle are fixed -if there are no interruptions- since AGVs' speed is assumed beforehand.

1.5 Thesis structure

In this section, a brief explanation of the different chapters of this report is presented summarizing essential points of different sections.

The current chapter of this thesis contains a description of the problem, aims and objectives, and limitations. Chapter 2 presents the literature review of the issues of vehicle scheduling and part feeding, including the previous works in this field. Additionally, subjects of discrete-event simulation and simulation-based optimization are covered. Chapter 3 covers the applied theoretical framework in detail. Moreover, the concept of multi-objective optimization and the selected algorithm for the optimization process are introduced. Following, the methodology of this project covered in Chapter 4, and it includes the research strategy, the philosophical paradigm, and the thesis methodology. This chapter also covers the simulation steps in detail, such as the problem formulation, model conceptualization, data collection, model translation, verification, and validation processes. The different what-if scenarios are discussed, as well. In Chapter 5, the obtained results are presented, analyzed, and discussed. Chapter 6 contains a discussion for the whole project and the results in particular. In the successive chapter, Chapter 7, the conclusions and the future work of this project are written. Section 8 presents different references for this project. The final chapter, Chapter 9, includes the various appendixes that are supplementary to this study.

2 Literature review

Simulation is a technique used as a tool for analyzing, designing, and improving organizations' systems. This technique has evolved, and its applications have grown considerably in the last decades (Uriarte et al., 2015 b). According to Ülgen and Upendram (2014), the simulation approach plays a vital role in designing an effective material handling system. They state that there has been an enormous growth of material handling technology and equipment types such as automated guided vehicles (AGV), electrified monorail systems (EMS), high-rise storage retrieval systems, computerized picking systems, computer-controlled conveyors and robots.

Moreover, the simulation approach used in many places such as hospitals, companies, and manufacturing plants , and it represents the tool of change that helps the management to make the right decisions. The simulation approach can be classified into four phases; the conceptual phase, the detailed design phase, the launching phase, and the fully operational phase (Ülgen and Upendram, 2014). Additionally, the simulation approach is applied in the industry field, and it is used to understand the system as well as to address intricate design, operational, and scheduling problems.

Another prominent approach is lean manufacturing, which is considered one of the most applicable approaches in the field of industrial systems. The core idea is to maximize customer value while minimizing waste. The ultimate goal is to provide absolute value to the customer through a perfect value creation process that has zero waste (Jones and Roos, 2009).

In addition to lean manufacturing, the optimization approach is used to find the extreme minima and maxima values of some objective functions. It has many applications, and for example, it gives the interaction between different parameters in the production process and gives the best arrangement of which the production methods can be applied, and the best values of different parameters can be obtained.

The combination of the three previous approaches (simulation, lean, and optimization) gives the best results because it enables the user to have a variety of possible alternatives to deal with the case of concern. Besides, this combination is suitable for different kinds of studies, and it is widely applicable in the industry because it helps to overcome many issues related to technical difficulties such as low throughput and high lead time values. A comprehensive insight into this combination and how each approach interacts with the two other ones are given in the theoretical framework chapter.

This chapter provides a comprehensive insight into previous works that dealt with material delivery to the line or parts feeding. In the process of assembly lines part feeding, the focus is on material delivery policies. The different categories of part feeding policies (lineside stocking, kitting, Kanban-based policies) are reviewed. Then, the problem of vehicle scheduling and routing is explored. Finally, the concepts of discrete-event simulation and simulation-based optimization are reviewed.

2.1 Internal logistics

Internal logistics is one of the most critical sections in manufacturing companies. It manages, arranges, and delivers the finished products. According to Boysen et al. (2015), in-plant logistics includes some processes starting with the receipt of parts, storing parts, sequencing of parts, and ending with delivery to the line and line-side presentation.

In agreement with Kilic and Durmusoglu (2015), the structure of material delivery to line or part feeding system consists of three main components which are storage of parts, transport of parts, and part feeding policies. The first component is the storage of parts, and it includes four subcomponents, which are storage type, storage policy, storage accessories, and picking methods and policies. The second principal component is the transport of parts, and it composes of two subcomponents, which are material handling equipment selection and material handling equipment routing. Baudin (2004) stated that the right selection of a material handling system is essential and substantial for the efficiency and effectiveness of the system. Besides, the routing of the vehicles is essential during the parts feeding process. The last component is parts feeding policies, and the next section gives a brief explanation to it.

2.1.1 Parts feeding policies

As stated in Kilic and Durmusoglu (2015), the last main component of parts feeding is the parts feeding policies, and they are determined as line side stocking, kitting, Kanban-based feeding, and hybrid feeding. The following four sections give a brief explanation for policies of line-side stocking, kitting, and Kanban-based feeding.

2.1.1.1 Lineside stocking feeding policy

As reported by Luo et al. (2017), the first subcomponent of the parts feeding policies is a lineside stocking supply system in which large quantities of materials are supplied to a decentralized collaborative center at one time. In other words, the material is delivered to assembly lines directly without storing them in a central warehouse, and this decreases the workload of operators in the middleman and alters the efficiency of distribution.

Da Cunha and De Souza (2008) presented an integer programming reformulation to indicate the number of cycles and items assignment to containers. Their study aimed to fulfill the demand at the minimum operation cost.

2.1.1.2 Kitting Feeding policy

In this approach of material handling, the required parts of assembly operation are repackaged in pre-stored kits before being delivered into assembly lines. According to Bozer and McGinnis (1992), the kit process is a particular aggregation of components that support one or more assembly operations for a specific order. In mixed-model assembly, each kit is prepared for a particular object which should be assembled. The kitting process could be classified as "stationary" and "traveling" (Bozer and McGinnis, 1992).

In the stationary kitting, the kit is delivered to one workstation and remains there until it is depleted; while in the traveling kitting, the kit moves with the assembly object and supports several workstations. Kitting method has several advantages in the different aspects that related to the manufacturing process as follows:

- **Staff-hour consumption:** Since the kitting could be presented close to the assembly lines, the time of fetching parts is reduced (Hanson and Medbo, 2011). Besides, kitting enables the assembler to have the required parts for a specific object without the need to search for them (Ding and Puvitharan, 1990; Johansson, 1991; Bäckstrand, 2009; Hua and Johnson, 2010).
- **Product quality and assembly support:** Since the assemblers do not need to be worried about what the specific part to be assembled, they could focus then on the assembly process itself (Bäckstrand, 2009). Besides the easiness, kitting provides to the assembly process, it facilitates the learning process and as a result, reducing the learning time and improving the product quality (Hanson and Brolin, 2013).
- **Flexibility:** Kitting offers more flexibility than the continuous supply method since only the necessary parts of one specific assembly object being presented at each workstation. Also, kitting supports the assembler by presenting the parts in a way that reflects the assembly operations (Bozer and McGinnis, 1992).
- **Inventory levels and space requirements:** Kitting requires less space for different part numbers that have to be stored in racks beside assembly stations due to the reason that just

parts that support the assembly of one object have to be presented at a time (Hua and Johnson, 2010).

2.1.1.3 Kanban-based feeding policy

As stated in Kilic and Durmusoglu (2015), this policy of part feeding depends on a decentralized storage area that serves as an intermediate point between the warehouse and the assembly lines. In the decentralized storage area (the supermarket), the required parts are handled to the assembly lines in containers, and the Kanban includes all information about the related parts that attached to each container (Faccio, 2014).

There are two significant aspects of Kanban-based feeding system design, such as the Kanban number determination and the supermarket design. Regarding Kanban number optimization, the most common objectives are the maximization of average cumulative throughput and the minimization of average lead time and average work-in-process (WIP). There are many studies related to Kanban number optimization, which are studied and reviewed under Just-In-Time (JIT) systems (Kumar and Panneerselvam, 2007).

A JIT milk-run part supply system is designed by Satoglu and Sahin (2013) to solve the routing and scheduling problems using the non-linear mixed-integer programming (MIP) model. The objectives were to minimize the total handled parts and the inventory costs, so the route construction algorithm was developed for this purpose.

According to Emde et al. (2012a), an exact polynomial-time solution was proposed to decrease the levels of line-side inventory. They applied that solution to address the tow train loading problem, and they gave limited capacities to vehicles.

Fathi et al. (2014) solved the problem of part feeding at mixed-model assembly lines concerning the Just-In-Time principle by introducing a mixed-integer linear programming model and a novel simulated annealing algorithm-based heuristic. The objectives of their study were to minimize the number of tours as well as the inventory level.

Fathi et al. (2014b) added a new constraint to the previous study, which is the delivery time. The method that the authors proposed was a scheme that incorporates a local search procedure in the memetic ant colony optimization and is combined with a heuristic algorithm.

De Souza et al. (2008) developed a model that indicates the appropriate quantity of each required item that has to be delivered during each trip of vehicles. They used the MIP model, and then they suggested a procedure that adapts the greedy randomized search.

Faccio et al. (2013) used a decentralized storage area (supermarket) to feed assembly lines with the required parts. They aimed to propose a framework comprises of an integrated approach for static and dynamic problems that deal with Kanban and Supermarket systems to solve problems related to assembly lines, and the tow train sizing and management. In their case study, they stated that two aspects should be designed correctly:

- The tow train size and management.
- The level of inventory for each part related to the Kanban number at different lines.

The main contribution to the knowledge of Faccio et al. (2013) is to provide a robust methodology that deals with complex supermarket/multiple mixed-model assembly line system. In that system, an integrated approach for the long and short-term is designed to solve the problem of fleet sizing and management.

According to Emde and Boysen (2012b), the different factors that related to the supermarket concept can be classified into four categories:

- Location, this determines the number and location of supermarkets that affect the parts number that each supermarket contains in order to deliver to the assembly lines.
- Sizing, this determines the number of transported vehicles, tow train in particular that assigned to the supermarket and decide their route and exactly where to start and where to finish.
- Scheduling, this means to assign a different schedule for each tow train for supplying parts to assembly lines.
- Loading, this is primarily about deciding on the number of parts to be loaded to assembly to assembly lines per trip. In other words, minimize the inventory at each station and avoid the shortage problem at the same time, and it requires having the capacity of each wagon as a constraint.

Battini et al. (2015) introduced a framework that deals with the material feeding into assembly lines. They divided the conceptual model into two sections; the first one aims at crucial input parameters and qualitative guidelines. The second part focuses on the transportation mode selection. They introduced a holistic classification of the in-house logistic problem:

- Warehousing modality either centralized or decentralized by using the supermarket.
- Transportation system; shuttle, tow train, or AGV.
- Line-side presentation of materials either using the traveling kit or station kit or lot-wise bins.

They drew some conclusions related to the part-feeding problem and transportation system choice. For the first part, they found that applying three different sub-phases is good and gives reliable outputs. For the second part, they Figured out that it is strongly affected by four parameters:

- How many meters that vehicle has traveled during each cycle.
- The number of working stations.
- The assembly line takt time.
- The number of traveling kits by station per takt.

Nourmohammdi et al. (2019) developed a mixed-integer programming (MIP) model to deal with the problem of integrated supermarket location and transport vehicle selection (SLTVPS). For large-sized problems, the writers proposed a hybrid genetic algorithm (GA) with the variable neighborhood search (GA-VNS). The authors compared the GA-VNS against the MIP, GA, and simulated annealing (SA) algorithm. The computational results of several generated test problems and a real case showed that the suggested GA-VNS surpass GA and SA while it gives an excellent estimation of the MIP solutions concerning computational time. The analysis of the final results shows that it is more advantageous to apply different types of transport vehicles than the identical vehicles of SLTVSP for this real case study.

Eskandari et al. (2019) addressed the problem of assembly line balancing and supermarket location problem by developing a two levels hierarchical mathematical programming model. In the first level, the authors resolved the stochastic assembly line balancing problem by minimizing the workstation numbers. In the second level, the issue of supermarket location was solved by optimizing the part feeding shipment, inventory, and installation cost. The results verified that the proposed model is beneficial in optimizing the configuration of assembly lines considering the performance measures of assembly line balancing and supermarket location problems.

2.1.2 Vehicle scheduling and routing

As reported by Bodin and Golden (1981), vehicle scheduling is a sequence of loading and unloading points during each trip associated with fixed starting and ending times. They define as well the vehicle routing as the action of the sequencing of pickup and delivery points that vehicles should follow to deliver the required materials to their final destination starting and ending at the depot.

Numerous studies that deal with vehicles scheduling and routing are available in the literature, Vaidyanathan et al. (1999) addressed the problem of vehicle routing to deliver materials in a JIT production plant. The objectives of their study were to minimize vehicle idle times and customer inventories. The writers proposed a heuristic approach consists of two stages to solve such a problem. In the first stage, they used a nearest neighbored algorithm to find possible routes, while they used a three-opt heuristic to improve these routes in the second stage.

Choi and Lee (2002) developed a dynamic feeding algorithm to solve the combined problem of loading, routing, and scheduling of tow trains for delivering materials to predetermined depots. The main objective of the previous study is to minimize the transportation time that is needed to feed lines with the required quantity of parts references.

Golz et al. (2012) addressed the problem of vehicle scheduling and routing in a case study of the automobile industry. The principal objective was to minimize the number of drivers required to operate vehicles, and in order to achieve that they developed a heuristic solution procedure consists of two steps. Firstly, transportation orders are identified based on the part code, production sequence, destination, and due dates. In the second step, those orders are consigned to tours of the shuttle system.

Kilic and Durmusoglu (2013) addressed the scheduling and routing problems with the objectives of minimizing transportation costs and WIP. They proposed a linear Mixed-Integer-Programming (MIP) model consists of two phases. In the first phase, routes are constructed, and workstations were assigned to them, while the second phase aimed to minimize the number of tours by increasing the times between sequent routes.

Kozan (2000) proposed a genetic algorithm in order to obtain the best assignment of delivery jobs and the sequence of deliveries for each vehicle. The results showed that this approach was successful in decreasing the total transportation time, including loading and unloading times.

A mathematical model, along with the network simplex algorithm, has been proposed by Fazlollahtabar and Hassanli (2018) to solve the problem of simultaneous vehicle scheduling and routing. The objectives of their study were to minimize the transportation cost and penalties of tardiness and earliness.

Zhuliang and Zhenxin (2014) suggested a mathematical model and hybrid particle swarm optimization algorithm to solve the physical delivery problem in mixed-models assembly lines (MMALs) using AGV's and automated storage and retrieval systems (ASRS). This study aimed to minimize the materials transportation costs, materials transportation time, and materials storage.

Rao et al. (2013) inspected the routing for one vehicle to supply parts to MMALs. They embraced the method of variant backtracking and a hybrid metaheuristic to minimize the total inventory and traveling costs. However, part-dependent inventory at different stations has not been taken into account in their work.

The JIT hoist scheduling of the automotive assembly lines problem was investigated by (Boysen and Bock, 2011). They used the bounded dynamic programming (DP) and simulated annealing (SA) heuristic approach to minimize the maximum weighted inventory level at workstations. In their study, part-dependent inventory weight was considered in the objective function. However, the author did not take into consideration the optimization of parts quantity within each delivery, and this led to material shortages.

The simulation approach is recommended to be used when the behavior of the system is complex, stochastic, and dynamic (Uriarte et al., 2015b). The discrete-event simulation is what can be used in case of studying part feeding systems and vehicle scheduling and routing because of the stochastic and dynamic nature that exists in such subjects. The next section gives a brief explanation of the discrete-event simulation approach, and some studies dealt with the problems of part feeding and vehicle scheduling and routing using such an approach.

2.2 Discrete-Event simulation

As mentioned above, the number of papers that talk about vehicle scheduling, in particular, are numerous. However, they concentrate on mathematical models or heuristic algorithms. On the other hand, a small number of papers that talk on the topic of vehicle scheduling and follow the discrete-event simulation approach is available. Negahban and Smith (2014) stated that only 290 papers published from 2002 to mid-2013 on the application of discrete-event simulation in manufacturing.

In agreement with Banks et al. (2005), a discrete-event system simulation (DES) is “the modeling of systems in which the state variables change only at a discrete set of points in time.” DES is presented in many real-world applications that include the analysis of manufacturing systems, healthcare, production lines, and more.

Lin et al. (2017) proposed a discrete-event simulation model that addresses the simultaneous scheduling of vehicles and machines in flexible manufacturing systems. The purpose of the model was to assess the performance of scheduling decisions after including some random factors like undefined process time, deadlock. They used a combination of GA and local search to explore the best design based on simulation output, and they embedded the Optimal Computing Budget Allocation (OCBA) with L-GA to allocate the number of replications for reducing simulation replications.
Lacomme et al. (2005) addressed the scheduling problem by introducing a technique so-called branch-and bound that was coupled with a discrete-event simulation model. The branch-and-bound focuses

on the sequencing of job-input, and this means to determine the order in which the job enters the manufacturing system. The discrete-event simulation model aims to evaluate this job sequence under machine dispatching rules and the given vehicle. The objectives of their study were to determine the job input sequencing and vehicle dispatching problem, and they included the dynamic behavior as well as the input and output buffer capacities as constraints.

Korytkowski and Karkoszka (2016) developed a discrete-event simulation model that contains an operator follows the milk-run method to deliver material to ten work stations that assemble different parts to form the final good. Some disturbances have been introduced to the model, such as time variability of technological operations and delays in the supply cycle. The decision variables that control the model like buffer capacity, supply cycle duration, and takt time presence or absence were introduced. The authors concluded that the operator of milk-run with a three-run bin system reduces the impact of variations and workstation starvation drops by one third. Besides, their study showed that there is no need to leave any safety time because the system will be rapidly compensated when any unforeseen disturbances are causing delays to appear.

According to (Uriarte et al., 2015b), the main drawback of the simulation approach is the amount of time that it takes to perform the different experiments. Moreover, the knowledge about optimum configurations of the system is not guaranteed. Hence, the optimization approach comes to address these issues, where it combined with simulation to form a practical approach so-called Simulation-Based Optimization (SBO). The next section gives a short explanation to SBO and some available studies that adapted it in the branch of internal logistics systems.

2.2.1 Simulation-based optimization for internal logistics system

Simulation-based optimization or numerical optimization is a method in which optimization techniques are integrated into simulation analysis Nguyen et al. (2014). Once a system is modeled, computer-based simulation provides information about the system's behavior using a method known as 'parametric simulation method.' In this method, the input of each variable is varied with keeping other parameters constant to observe the effect on the designed objectives. This is time-consuming and results in partial improvement because of the complex interactions of input variables on the results. Hence, numerical optimization represents a perfect solution to such a problem since it helps with finding the optimal solution with minimum computational time (Nguyen et al., 2014).

Matta (2008) presented mathematical programming representations to describe the behavior of a discrete-event simulation-based optimization system. The author proposed three formulations to solve the buffer allocation problem in flow lines with finite buffer capacities. The three formulations were an exact mixed-integer linear model, an approximate linear programming model, and a stochastic programming model. The results showed that the computational time required to solve the problem of the allocation could be significantly reduced by using these formulations.

Mahfouz et al. (2011) developed a simulation-based optimization model to evaluate the lean principles in packaging manufacturer with regards to three performance measures, namely WIP, workforce utilization, and cycle time. They concluded that the demand rate seemed to have a contradicting effect on the three performance measures, and the minimum cycle time and WIP can be achieved when applying a low demand rate.

Pichitlamken and Nelson (2002) proposed a simulation-based optimization algorithm where a discrete-event simulation is used to measure the performance of the system. The objective of their study was to maximize the average output of a flow line by indicating the best buffer allocation and service rates. The proposed framework substantiated its effectiveness in achieving an excellent empirical performance while maintaining a global convergence guarantee.

Through a case study, Syberfeldt and Lidberg (2012) developed a simulation-based optimization model of an engine manufacturing line. The objectives of this study were to maximize machine utilization and minimize bind capital. For this purpose, they used one of the metaheuristic algorithms so-called Cuckoo search to perform the simulation-based optimization. The results showed that the combinatorial nature of the optimization problem causes difficulties for the Cuckoo search algorithm and that algorithm best suits for continuous optimization problems.

A review of the literature revealed that internal logistics had been a hot topic for scholars in recent years due to its significance in manufacturing and industrial fields. In this regard, this study tackles the problem of vehicle scheduling by developing a discrete-events simulation-based optimization model that depends on kitting as the feeding policy.

It is worth noting that the improvement criteria considered in this study are to minimize the number of vehicles and inventory levels while disallowing shortage. Moreover, the vehicle capacity is considered as a constraint in this study. The next chapter explores the theoretical framework and explains the concept of multi-objective optimization using the NSGA algorithm since the model is a simulation-based optimization one.

3 Theoretical framework

In this chapter, a comprehensive description of the theoretical framework, which is Lean Simulation-based optimization (LeanSMO), is presented. Moreover, the concept of evolutionary multi-objective optimization and the selected algorithm to perform the optimization process, which is the Non-Dominated Sorting Genetic Algorithm (NSGA-III), are described.

3.1 Lean Simulation-based Optimization Framework

The theoretical framework for this project based on the Lean Simulation-based Optimization framework proposed by (Uriarte et al., 2015b). The combination of Lean, Simulation, and Optimization approaches is advantageous in dealing with manufacturing problems because it enables the user to have a variety of feasible options to deal with a particular case, and this is because of the effectiveness of that combination. This combination helps in overcoming the weaknesses of each previous approach and continuously improves the processes in a better way than applying them alone (Uriarte et al., 2015b). The advantages of each approach would be mentioned in separate sections in order to give a clear insight into the superiority of this framework.

3.1.1 The advantages of the Lean approach

Lean manufacturing is undoubtedly one of the most applicable approaches in the field of industrial systems. The core idea is to maximize customer value while minimizing waste. The ultimate goal is to provide absolute value to the customer through a perfect value creation process that has zero waste. Lean thinking has a primary effect on the system being developed and that effect represented in changing the focus of management from optimizing separate assets and the vertical department to optimizing the flow of products and services through value stream that flows horizontally across the department to customers (Jones and Roos, 2009).

Moreover, lean thinking is flow focused orientation; this means that it values the flow of the different operations, which will lead to the final product. More broadly, the flow must go horizontally from the last process to the earlier one following the pull system focusing on the whole production process, not on each process in isolation.

Furthermore, lean concerns on the cost, lead time, and value-added percentage. The less lead time and cost are for the operation process to be done, the more waste will be removed, and the more value-added work obtained, the more waste will be eliminated in the whole system.

3.1.2 The advantages of Simulation

The simulation process gives the interaction between different parameters in the production process. It gives the relationship of different variables and how they affect each other, and it has many advantages, such as (Uriarte et al., 2015b):

- Experimentation could be conducted on the part of an industrial system or even on the whole system without the need to disturb the actual system. The simulation process can be done in a compressed time and on an expansion time by activating the slow-motion option.
- The analysis of new machines, the physical layout could be run to determine the degree of profitability in case of acquiring new equipment.
- Eases the analysis of complex systems, reducing the requirements of analytic analysis.
- The simulation model offers the visualization feature by which the designer can demonstrate the new design and explain the improved alternatives of the existing system.
- How different variables interact with each other and what are the possible reasons that make a system operates in a particular way as well as bottleneck detection could be obtained by running the simulation process.
- Hypotheses about why and how certain phenomena occur can be tested.
- What-if scenarios can be tested, and the best one that is appropriate to the case under study could be presented to the management.

3.1.3 The advantages of Optimization

Finally, optimization helps in improving the result that derived from the simulation model, and it is a very effective way since it has some intrinsic advantages such as (Uriarte et al., 2015b):

- The information gained from the optimization process is precious for the decision-makers, especially when the conflicting objectives have to be analyzed.
- The simulation process alone does not guarantee to get the optimum results, and the process of multiple what-if scenarios takes a long time. Thus, using the simulation in combination with the optimization is the best solution.
- The optimization results will show if the simulation model is correct or not.

In the next section, a brief explanation about how lean, simulation, and optimization can be interconnected with different purposes is presented (Uriarte et al., 2015b).

3.1.4 The interaction between lean, simulation and optimization with different purposes

The aim of lean, simulation, and optimization framework is to support decision-makers when designing and improving their systems. The combination of the three previous approaches helps in getting rid of the drawbacks of each approach. There are three purposes in which lean, simulation and optimization are interacting with each other as follows:

- **Educational purpose:** The simulation model is used to teach lean concepts to employees of any organization. Besides, the simulation model can be used to train personnel in different working procedures of the company.
- **Facilitating purpose:** The simulation model can be used to ease the discussion during Kaizen meetings in which the improvement process is discussed continuously by the concerned team responsible for that particular process. Besides, it can be an alternative for Value Streaming Map to help in the understanding of the process of manufacturing operations.
- **Evaluation purpose:** The simulation model can be used to evaluate the entire process in different stages, as follows:
- *Evaluation of the current state:* The current state is the starting point for any simulating project, and the simulation model can play a principal role in clearing the picture of the real situation by providing a quantitative and dynamic evaluation.
- *Evaluation of the future target condition:* the simulation model can offer the opportunity to analyze the different possible scenarios before the need to implement them in the basic layout and check the alternative results. Besides, lean principles could be executed through this model, such as JIT, Pull or Push, CONWIP...
- *Evaluating the implementation:* The simulation model also has a significant role in evaluating the implemented desired design by showing the results and ambitioned outcomes to check the success of that design. Additionally, failures to implementation can also be evaluated by comparing the current state with the future condition and run the optimization for having the optimal configuration.

The following figure, **Figure 2**, illustrates the LeanSMO framework and how lean interacts with the simulation-based optimization (SMO) for each stage of LeanSMO.

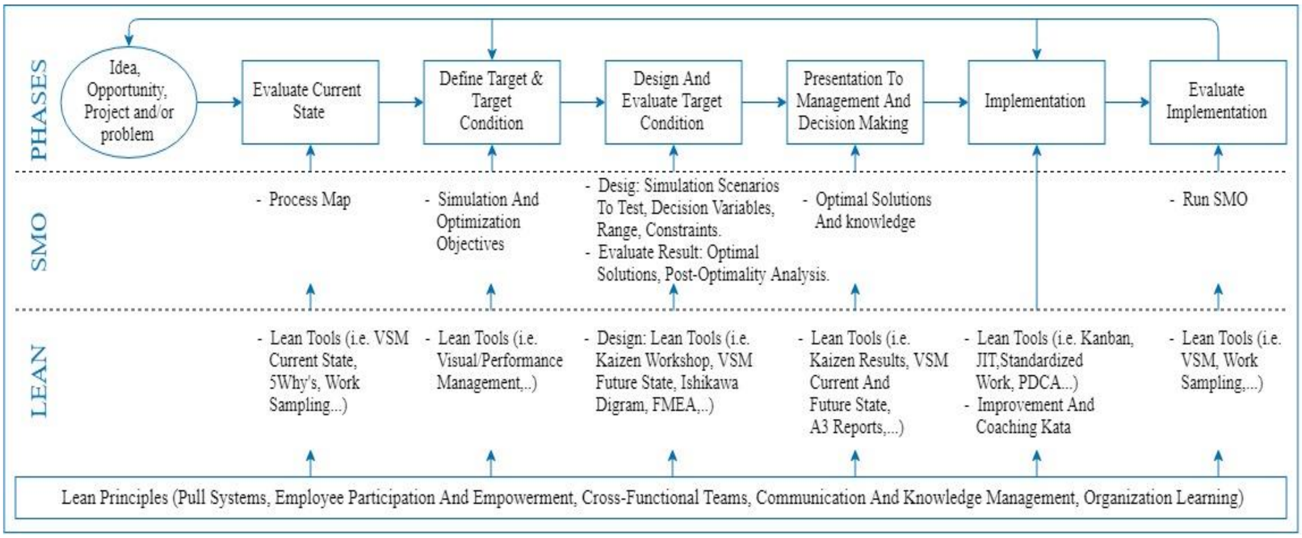


Figure 2. Lean and Simulation-based Optimization framework (Uriarte et al., 2015b)

As appreciated in figure 2, the role of lean tools and SMO are presented for every step of the LeanSMO framework. In the phase of target condition design and evaluation, the Kaizen workshop, for instance, can be selected as a lean tool to assess the results of designed simulation scenarios and improve the best situations by performing an optimization process. The next section explains the evaluation purpose of the LeanSMO framework.

3.1.5 The evaluation purpose of LeanSMO framework

The main aim of this section is to provide a powerful tool to enable decision-makers to analyze different possible scenarios by combining lean, simulation, and optimization in different ways and different stages (Uriarte et al., 2015b). The description of different evaluation steps can be discussed accordingly.

- **Evaluate current state:** The primary purpose of this stage is to get an insight into the actual system situation. Lean tools such as Value Stream Mapping are very significant in this stage to enable the designer to develop the simulation model. In this step, the required data is collected to build the simulation model. In this case study, some data collection techniques like interviews and existed documents have been used to gather the necessary data about the current state.
- **Define target and target condition:** The main aim of this stage is to define the target and target condition. In this stage, objectives will be set as the target condition that has to be done or achieved. As mentioned before, in the thesis objectives section, the main objective is to

introduce a new material handling system for the proposed layout of the main shop floor for the factory.

- **Design and evaluate target condition:** The main goal of this stage is to have alternative system configurations that match the predefined target condition. Improvement options, design rules can be obtained to treat them as input for decision making. In this stage, the conceptual model is translated into the final simulation model that satisfies all design requirements.
- **Implementation:** The fundamental purpose of this step is to execute the future scenario, which previously defined as a target condition. Lean principles like poka-yoke, JIT, Kanban, and 5S… are significant to help to evaluate the obtained results. This step is out of the scope of the thesis; therefore, the last step in this thesis is to design and evaluate target conditions.

The previous steps of the evaluation purpose of the LeanSMO framework are presented in **Figure 3**.

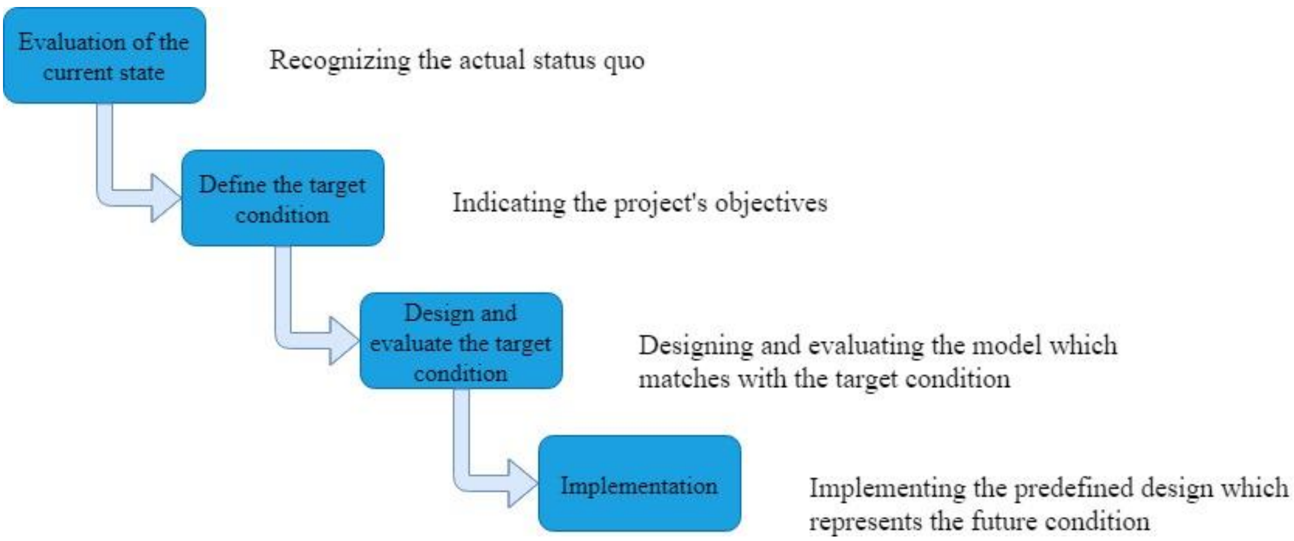


Figure 3. Steps of evaluation purpose of LeanSMO framework (Uriarte et al., 2015b)

As appreciated in Figure 3, the first step is to recognize the current conditions to be able to indicate the project’s goals. Then, the phase of model designing and evaluating starts. After that, a decision would be made for implementation or not after assuring that the model satisfies the design requirements. The next sections provide a full description of evolutionary multi-objective optimization, the concept of dominance, the Non-dominated sorting Genetic Algorithm (NSGA-II), and its extension (NSGA-III).

3.2 Evolutionary Multi-Objective Optimization (EMOO)

A multi-objective optimization problem (MOO) is a process of altering several objective functions, whether to maximize or to minimize them (Deb, 2011). The general form of (MOO) could be stated as follows:

$$\begin{aligned}
&\text{Minimize/Maximize} \quad f_m(x)\,, && m = 1, 2\ldots, M;\\
&\text{Subject to} \quad g_j(x) \geq 0, && j = 1, 2\ldots, J;\\
&\qquad h_k(x) = 0 && k = 1, 2\ldots, K;\\
&\qquad x_i^{(L)} \leq x_i \leq x_i^{(U)}, && i = 1, 2\ldots, N;
\end{aligned}$$

The interpretation of above expression is, the optimization process of function F of a defined variable X and M objectives could be achieved under a set of inequality and equality constraints (J, K) that must be satisfied and within the upper and lower variable bounds.

The objective function could be any aim that must be achieved or satisfied in the study area, and in this case, the manufacturing field is the subject of interest. The most common ends in the industrial field are the great trade-off between throughput and WIP beside the lead time and buffer allocation. In multi-objective optimization, the set of compromise optimal solutions is found by considering all objectives to be important. Then, the user can use higher-level qualitative considerations to make a choice. The main goals of multi-objective optimization could be as follows (Deb, 2011):

- Looking for the solutions that lie on the Pareto-optimal front, which can be convex, concave, or fragmented.
- Looking for solutions that are diverse enough to represent the whole Pareto-optimal front.

The Pareto-optimal front is a set of solutions that are not dominated by the rest for the same set of functions (Sumper et al., 2013). Thus, Pareto optimal solutions can be seen as an optimal trade-off between objects because, under the concept of optimality, it is impossible to improve one objective without degrading the others. In the Pareto-optimality problem, four high scenarios could be generalized and used to solve any multi-objective cases. The following figure, **Figure 4**, shows those scenarios by displaying Pareto-optimal front, ideal, and non-ideal solutions for four possible combinations of the two kinds of objectives (Shahhosseini et al., 2016).

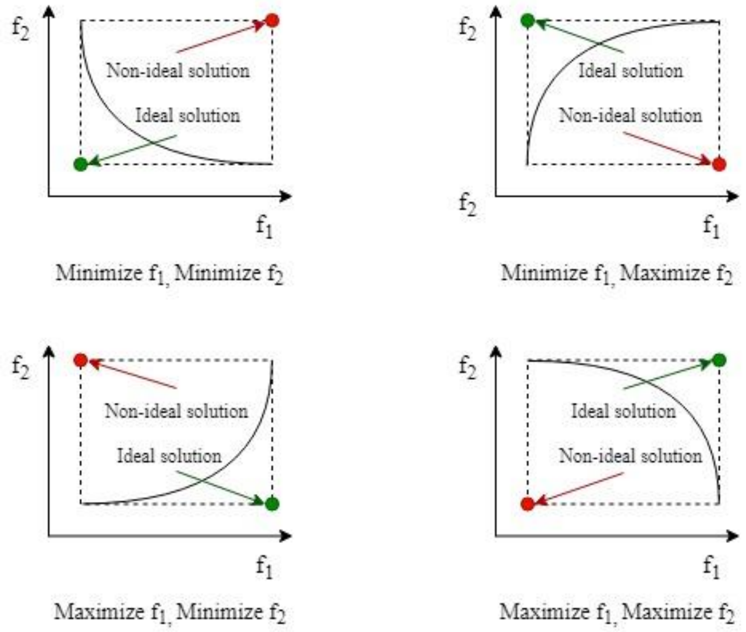


Figure 4. Pareto set for four combinations of two types of objectives (Shahhosseini et al., 2016)

3.2.1 The concept of dominance

The concept of dominance is the base principle in multi-objective optimization field, and the dominated solution must meet satisfied two conditions (Deb, 2011):

- The dominated solutions are not worse than the other solutions for all objectives. Thus, all solutions are compared based on their objective functions.
- The dominated solutions are better than the other solutions in at least one objective.

3.2.1.1 The mathematical representation of the dominance concept

For any $x_1, x_2 \in S$, the solution x_1 dominates x_2 if and only if,

- Fi (x1) ⋫ Fi (x2) ∀ i = 1,2, 3..., M → x1 is not worse than x2 in any of the objectives.
- ∃ j such that Fj (x1) ⊲ Fj (x2) ∀ j ∈ {1,2, 3..., M} → x1 is better than x2 in at least one of the objectives.

The denotation of "x1 dominates x2" is x1 ≼ x2. For the case in which x1 is better than x2 in all objective functions, then it is possible to say that x1 is strictly dominated x2, and the denotation is x1 ≺ x2. If neither x1 ≼ x2 nor x2 ≼ x1, then it could be read as "x1, x2 are equivalent" or "x1, x2 are non-dominated concerning each other," and the denotation is x1 ∥ x2.

3.2.2 Multi-Objective Optimization Using NSGA-II

In this section, an evolutionary multi-objective optimization algorithm so-called Non-Dominated Sorting Genetic Algorithm "NSGA-II" is explained. Kalyanmoy Deb introduced this algorithm, and it proved its effectiveness in the field of multi-objective optimization and finding the optimal Pareto set in particular. The NSGA-II procedure is performed as follows:

I. The algorithm starts with **population initialization** in which the population is initialized based on the range of the problem. The parent population (P_t) is initialized, which related to the input variables. Then population (R_t) at time t is created by joining the offspring population (Q_t) and parent population (P_t) where the child population is produced from parent one by genetic operators such as crossover and mutation (Deb et al., 2002).

II. Afterward, for the initial population (R_t), the **non-dominated sort** takes place in a manner that elitism from the previous generation is preserved (Deb et al., 2002):

- For each individual p in main population P:
    - Initialize $S_p = \emptyset$; this is the set of solutions in P that p dominates.
    - Initialize $\eta_p = 0$; this is the number of solutions that dominate P.
    - For each individual q in P
        - If p dominates q then
            - Add q to the set S_p, $S_p = S_p \cup \{q\}$.
        - Else if q dominates p then
            - Increase the domination counter for p, $\eta_p = \eta_p + 1$.
    - If $\eta p = 0$, this means that no individuals dominate p, then it would be the first rank, $P_{rank} = 1$. The first rank is updated, $F_1 = F_1 \cup \{p\}$.
- The previous step is repeated for the whole individuals in the main population set P.
- Initialize the front counter to one, i =1.
- While $Fi \neq \emptyset$, do the following:
    - Set $Q = \emptyset$ for sorting solutions of the next rank $(i + 1)^{th}$.
    - For each individual p in F_i front do
        - For each q in Sp
            - Decrease the domination count for individual q, $\eta_p = \eta_p - 1$.
            - If $\eta_p = 0$, then none of the individuals in the subsequent fronts dominates q. Thus, the set Q is updated, $Q = Q \cup q$.
    - Increase the front counter by one.

- Set $F_{rank} = Q$.

III. The next step is to apply the **Crowding Distance Comparison** for the same rank, which does not fit entirely in the next set of the parent population (P_{k+1}). This step can be explained in more details as follows (Deb et al., 2002):

- For each front F_i, n is the number of individuals
  - Initialize the distance to be zero for all the individuals, $F_i(d_j) = 0$, where j corresponds to the jth individual in front F_i.
  - For each objective function m
    - Sort the individuals in front F_i based on objective m, i.e., I = sort (F_i, m).
    - Assign infinite distance to boundary values for each individual in F_i, i.e., $I(d_1) = \infty$ and $I(d_n) = \infty$.
    - For k = 2 to (n-1)

$$\boldsymbol{I(d_k) = I(d_k) + \frac{I(K+1).m - I(K-1).m}{f_m^{max} - f_m^{min}}}$$

Equation 1. Crowding distance calculation

Where, I(k).m is the value of the m^{th} objective function of the k^{th} individual in I.

Thus, the idea behind the crowding distance process is sorting solutions of the same rank in decreasing order. The higher crowded the solution is, the lower the crowding distance would be, and this is against the second feature of NSGA-II, which indicates that the solutions should have a crowded high distance (more diverse).

IV. The successive step is the best solution **Selection** process, and this step is performed after sorting all individuals based on non-dominated then crowding distance value. The selection is carried out using a crowded-comparison-operator or crowded tournament selection as follows (Deb., 2002):

- Non-dominated rank in which individuals have their rank as $P_{rank} = i$.
- Crowding distance F_i (d_j).
  - If $P \prec q$
    - $P_{rank} \prec q_{rank}$.
      - If $q \prec p$

- $q_{rank} \prec P_{rank}$.
  - If p and q fall in the same rank then
    - If I (p) > I (q), then p wins the tournament.
    - If I (p) < I (q), then q wins the tournament.
    - If I (p) = I (q), then q or p are chosen randomly.

V. The next step is **Genetic Operators Applying**; the two genetic operators are Simulated Binary Crossover (SBX) and polynomial mutation (Deb et al., 1995).

- Simulated Binary Crossover (SBX): This kind of crossover is the best fit for the case study of this project because it is suitable for problems that were having discrete-continuous search space like the current project. Moreover, Deb et al. (1995) argued that this type of recombination found to be particularly useful in problems having multiple optimal solutions with a narrow global basin. In this type, the mean value of children is equal to the mean value of parents, and the two resulted children are symmetric concerning the two parents. The steps of (SBX) could be written as follows:
  - Pick pairs of individuals from the top of M_k.
  - Generate random number r between 0 and 1.
  - If $r \leq p_c$ then
    - Assign a value of 0.5 to the crossover probability.
    - Calculate the probability distribution of the spread factor:

$$\boldsymbol{p(\beta)} = \begin{cases} \mathbf{0.5(\eta_c + 1).\beta^{\eta_c}} & \boldsymbol{if\ \beta \leq 1} \\ \mathbf{0.5(\eta_c + 1).\frac{1}{\beta^{\eta_c + 2}}} & \boldsymbol{Otherwise} \end{cases}$$

Equation 2. The probability distribution of the spread factor

Where, $\boldsymbol{\eta_c} \geq 0$ is the distribution index, $\beta = \left|\frac{C_2 - C_2}{P_1 - P_2}\right|$ represents the spread factor.

- Choose a random number u between 0 and 1.
- Calculate the β_u as follows:

$$\beta u = \begin{cases} (2u)^{\frac{1}{\eta c+1}} & \text{if } u \le 0.5 \\ \left[\frac{1}{2(1-u)}\right]^{\frac{1}{\eta c+1}} & \text{Otherwise} \end{cases}$$

Equation 3. The spread factor of random number u

- Create children using the following formulas:

$C_{1,k} = 0.5[\ (1\text{-}\beta_k).\ P_{1,k} + (1+\beta_k).\ P_{2,k}\ ].$

$C_{2,k} = 0.5[\ (1+\beta_k).\ P_{1,k} + (1\text{-}\beta_k).\ P_{2,k}\ ].$

Where $C_{i,k}$ is the i^{th} child with K^{th} component, $p_{i,k}$ is the selected parent.

- Else if $r > p_c$
  - Place the two individuals directly in R_k.
- Repeat all previous steps until R_k has the population size N.

- Polynomial mutation (PM): After applying (SBX), the mutation operator can be performed. The polynomial mutation is the best fit with this case study due to the reason that it enables to mutate the whole search space of the decision variable even though the value to be mutated is close to one of the boundaries. As a result, the optimization has better chances of escaping the local optima and modify a solution when it exists on one of the two boundaries. The steps of (PM) could be written as follows:

  - Pick each from the top of R_k.
  - For each variable P_k having the lower and upper bounds $[P_k^{(L)}, P_k^{(U)}]$ do:
    - Generate random number r between 0 and 1.
    - If $r \le p_m$ then
      - Let P_1 be the parent.
      - Create the child using the formula of probability distribution:

$$(\delta) = 0.5(\eta_m + 1)\ (1 - |\delta|)\eta_m$$

Equation 4. The probability distribution of polynomial mutation

Where: $\delta = \frac{C_1 - P_1}{P_K^{(L)} - P_K^{(U)}}$

- Create a random number u between 0 and 1.
- Calculate the polynomial distribution as follows:

$$\boldsymbol{\delta_k} = \begin{cases} (2u)^{\frac{1}{\eta_m+1}} - 1 & \text{if } u < 0.5 \\ 1 - [2(1-u)]^{\frac{1}{\eta_m+1}} & \text{otherwise} \end{cases}$$

Equation 5. The absolute difference in offspring values

where $\eta_m \geq 0$ distribution index, u: a random number between (0,1).

- Create a child using the following formula:

$$C_1 = P_1 + \left(P_K^{(L)} - P_K^{(U)}\right)\delta_k$$

VI. The last step is the **Recombination and Selection.** The children population is joined with the current generation population, then the selection is performed based on the non-domination, and this ensures the elitism. The whole previous steps should be repeated to generate subsequent generations. The following figure, **Figure 5**, shows a representation of NSGA-II procedure, according to (Shahhosseini et al., 2016).

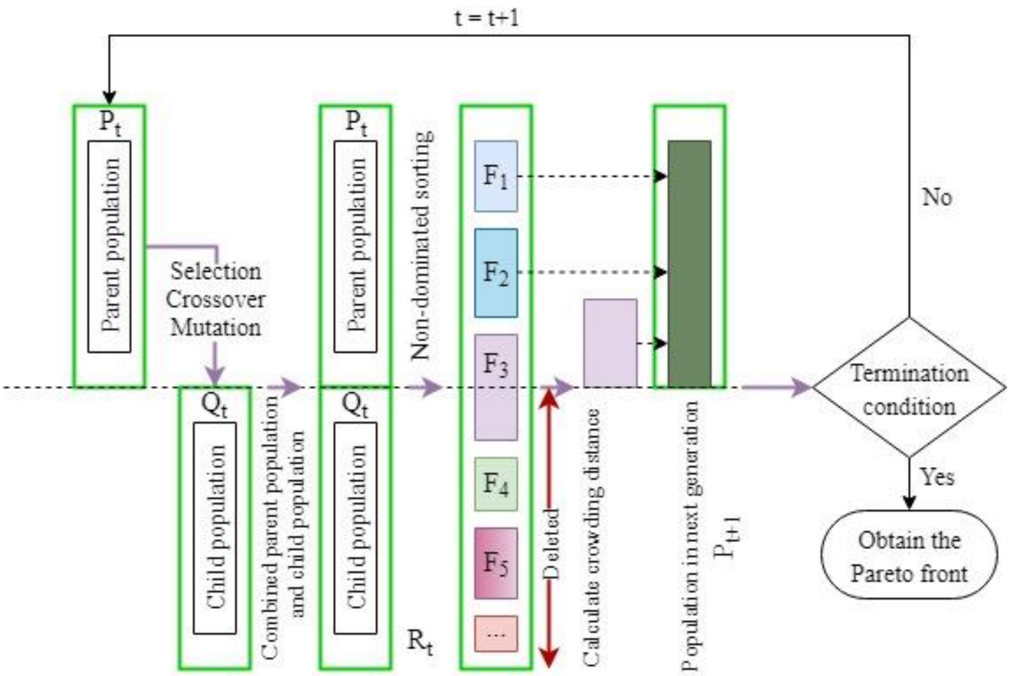


Figure 5. Schematic of the NSGA-II procedure (Shahhosseini et al., 2016)

3.2.3 NSGA-III

It is an extension of NSGA-II, so all operators are almost the same. However, the selection parameter differs significantly from NSGA-II, wherein the best members from the last non-dominated front are selected regarding the supplied reference points (Ibrahim et al., 2016).

First, the values of different objectives are normalized regarding members of S_t, which is the selected population, including the last non-dominated front F_t. Then, the population members of S_t and F_t are associated with a reference point that is closest to a population member in the objective space. After that, the associated population members from $P_{t+1} = S_t$ are counted. The procedure of NSGA-III is explained briefly, as follows (Ibrahim et al., 2016):

- P_0 = Initialize population () % uniform random
- Z^{γ} = Generate Reference Points ()
- **While** termination criteria are not met, **do**
- $S_t = \emptyset$, i = 1; S_t: the population selected so far including the last non-dominated front F_l
- $R_t = P_t \cup Q_t$; R_t: the combined population, Q_t: offspring population, P_t: parent population
- (F_1, F_2…) = Non-dominated-sort (R_t)
- **Repeat**
- $S_t = S_t \cup F_i$ and i= i+1
- Until $|S_t| \geq N$; N: the population size
- Last front to be included: $F_l = F_i$
- **If** $|S_t| = N$ **then**
- $P_{t+1} = S_t$, **break**
- **Else**
- $P_{t+1} = U_{j=1}^{l-1} F_j$
- Pointes to be chosen from F_l : $K = N - |P_{t+1}|$
- Normalize objectives

  Normalize f^n, S_t, Z^r, Z^s, Z^a ; Z^r:normalized hyper-plane.
- Associate each member **s** of S_t with a reference point: $[\pi(\boldsymbol{S}), d(\boldsymbol{S})]$= Associate S_t, Z^r%

  $\pi(\boldsymbol{S})$: closest reference point, d: distance between **s** and $\pi(\boldsymbol{S})$
- Compute niche count of reference point $j \in \rho_j = Z^r : \sum_{s \in S_t / F_l} ((\pi(\boldsymbol{S}) = j\ ?\ 1 : 0)$
- Choose K members one at a time from F_l to construct P_{t+1} Niching (K, $\rho_j, \pi, d, Z^r, F_l, P_{t+1}$)

- **End if**
- **End while**

The main goal of the NSGA-III algorithm is to generate well-converged and well-distributed sets of solutions over multiple runs. As in NSGA-II, four control parameters are also introduced, and they are SBX probability, polynomial mutation, crossover distribution index, and mutation distribution index.

As reported by Mytilinou and Kolios (2017), NSGA-III behaves better when the number of objectives is more than four parameters, and the results appear to be more uniform, and specific pairs of objectives are complete in terms of the distances between any points and more precious in terms of some points within a relatively narrow area.

4 Methodology

In this section, the research strategy of this project, the philosophical paradigm, and the simulation method are presented. Additionally, the steps used to develop this project are described; this includes steps such as data collection, the conceptual model, the simulation model, and what-if scenarios.

In **Figure 6**, it is possible to see how the general tasks of this project are performed. Every step has to be developed in order to reach the correct performance of the improvement methodology.

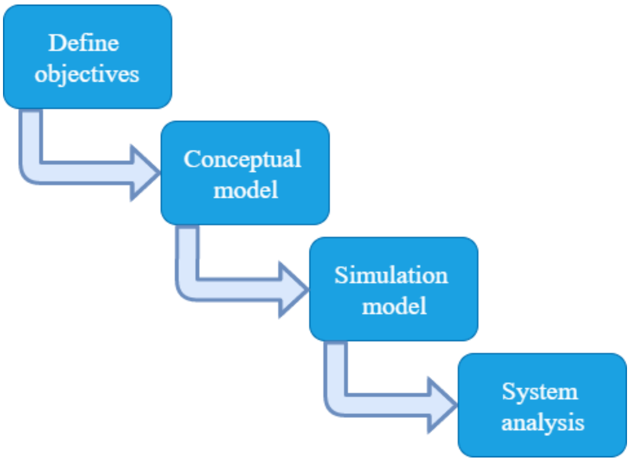


Figure 6. Project implementation steps

As shown in Figure 6, the first step in this project is the definition of the objectives. They have been defined based on the requested goals and tasks of the project. With these objectives, it is possible to get a general idea of the assignment of this project. It is crucial to take into account the necessary processes, resources, and staff into the simulation model.

The next step is the construction of the conceptual model; it requires significant attention to avoid possible changes that come afterward. For this reason, when the conceptual model is accurately studied, built, and checked, it is possible to go to the next step: to build the simulation model.

In the step of constructing the simulation model, all the required operations are represented to understand the system. The model has to be validated and verified to check that the simulation represents the system as it is, without any failure, and with all requirements needed to build up new scenarios.

The next step is to perform system analysis. The model has to be revised to find all possible weaknesses of the real system. In this part of this project, "what-if" scenarios are defined to check the possible improvements in the existing configuration of the system. In the next section, the research strategy of this project is presented. Then, the philosophical paradigm required for this research strategy is presented after then.

4.1 The research strategy

The appropriate research strategy for the project is design and creation because the primary outcome is an artefact or an IT product. The IT product is the developed simulation model that represents a tangible end-product. However, this study focuses on the development method implemented to build the simulation model. In more detail, a comprehensive explanation of the different steps followed to get this study finished is presented. After analyzing the system and based on the different what-if scenarios, the model then has to be optimized, and the final results indicate the functionality of the developed model. This strategy of design and creation is a problem-solving approach, and it generally consists of five repeated steps:

- **Awareness:** The first step is to recognize the situation, then try to suggest some possible solutions. The number of vehicles that visit assembly lines and the inventory level at every lineside can be the main objectives that should be addressed.
- **Suggestions:** As the main goals are indicated, the suggestions for the defined problem can be set. IT product, which is a simulation model, is developed to tackle and achieve the objectives.
- **Development:** The IT artefact has to be developed based on a theory, and this theory must be rigor and valid. For the simulation model, a lean and simulation-based multi-objective optimization was considered to be the best approach in this project since it has all the required steps, which consist of the leading theory.
- **Evaluation:** The resulted product then has to be evaluated to test and check its validity. For the simulation model, the responsible company persons of the project and simulation and lean experts are involved in the verification and validation processes.
- **Conclusion:** If the work is valid, then it will be written up and identified to make it possible for future students getting benefit from it.

4.2 The philosophical paradigm

The appropriate paradigm for that strategy is positivism. Since positivism embedded the scientific method as an approach to research the natural sciences rather than the social world as in interpretivism. The two underlying assumptions in the scientific method are as follows:

- The world is ordered and regular, not random.
- It can be investigated objectively.

Moreover, the characteristics of positivism make it a suitable paradigm to follow since the researcher observes the measurement and modeling way to discover the status quo by making observations and measurements and producing different hypotheses, theories of how this world works. On the other hand, it depends on the quantitative data analysis to prove the mathematical model and statistical analysis.

Furthermore, the researcher will objectively analyze data and outcomes without interfering with personal beliefs and values inside the final reports, and this what makes the final work valid and reliable for the scientific community. All mentioned above have been applied in this project to reach the final results and discuss them.

Firstly, the first step in this project was meditating the current status or the real situation. It was done through monitoring the situation as it is and take some measurements such as the daily demand, the processing time for each workstation, the current method of material delivered, number of shifts. All these data are quantitative data and information.

Secondly, the theory was evaluated at the end of this project. Therefore, the scientific method is the general framework in this project, and this method is what positivism includes. As a result, positivism is a suitable and appropriate philosophical paradigm to follow and adapt.

The core of the methodology is compound by building a simulation model of the main shop floor to analyze the layout and possible configuration of the logistics systems. The simulation method is presented in the following sections.

4.3 The simulation method

As mentioned in the theoretical framework section, the LeanSMO approach is used to build the simulation model. The simulation types are numerous; however, Discrete-event system simulation (DES) is the one chose in this project due to the size and complexity of systems to analyze. As claimed by Uriarte et al. (2015b) DES is a discrete, stochastic, and dynamic simulation model, and every term is explained below:

- **Discrete:** Basically, it means the state variables change at a discrete set of points in time like products in an assembly line.
- **Stochastic:** A system that has more one than a random input variable so that the result will be random as well.
- **Dynamic:** This means that the system changes as time goes by.

The steps to build a simulation model are presented in the following section.

4.4 The simulation steps

The steps of simulation are explained in general so that they could be applied for any project type. After that, it would be demonstrated for this project. The flow chart of simulation steps is done according to the study of Banks (Banks et al., 2005), and they are reprinted in the following figure, **Figure 7**, and explained in the following sections.

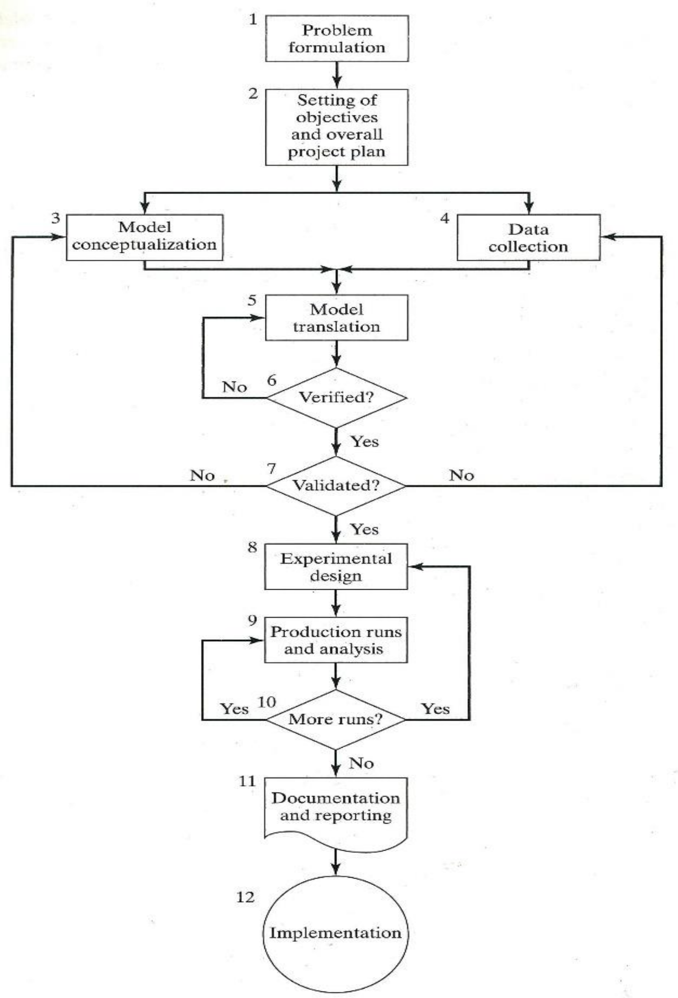


Figure 7. Simulation steps (Banks et al., 2005)

4.4.1 Problem formulation

As reported by Chung (2003), the formal problem statement includes texts of different situations of the manufacturing process, such as:

- **Increasing customer satisfaction:** This includes reducing waiting queues, delivering materials on time, or reducing the number of backlogs.
- **Increasing Throughput:** This means that the number of products that could be processed over a particular period can be increased or even includes the elimination of bottleneck processes.
- **Reducing waste:** This includes any action that does not add any value to the work and causes a decrease in net profits. Besides, the inability to bring the products on time also is considered as waste.
- **Reducing WIP:** This involves insufficient resource capacity and poor operating policies. By reducing WIP, the needed storage space could be reduced. Therefore, the process cost will be decreased as well.

Numerous tools could be used to form the problem statement, such as the fishbone chart and Pareto chart. This study adopts the fishbone chart as a tool to indicate the problem statement. In the fishbone chart or cause-and-effect diagram, the whole possible sources of the problem are discussed to obtain the possible scenarios of solving them. It contains branches or bones, and each one refers to a different category. For instance, in the manufacturing field, the significant branches could be man, machine, material, and method. **Figure 8**, shows the fishbone chart of this study:

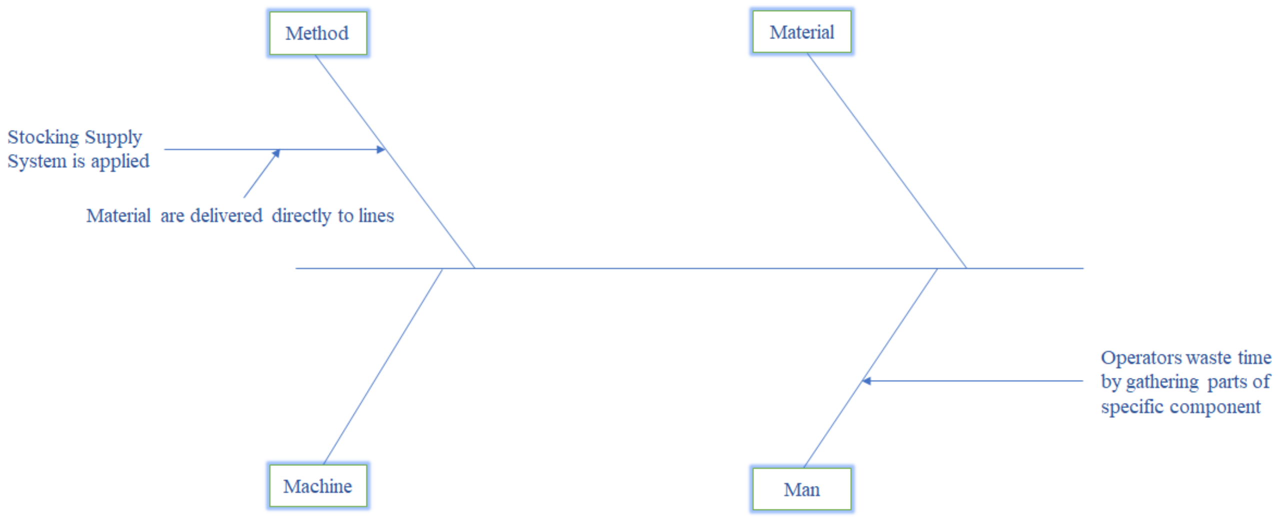


Figure 8. Fishbone chart

As shown in the previous figure, the different sources of a specific difficulty distributed on a particular bone based on the categories that they belong to. For the man bone as an example, it might include maintenance people or engineers, supervisors, or technicians.

For the machine bone, it could include all operations that together represent the whole manufacturing process. The branch of material could include all parts that have to be processed to get the final goods. Finally, for the method branch, it could include the currently applied method of the manufacturing process in each stage.

As mentioned in this study, the company follows the stocking supply policy where the material is delivered to assembly lines and stored in line-side buffers. Firstly, this leads to waste in the time since operators at assembly lines consume more time fetching parts to be assembled. Secondly, the stocking supply policy results in imbalanced inventories because the material is continuously supplied to operation lines. Hence the kitting feeding policy is adapted to overcome these two problems since it saves the time that the assembler wastes in searching for the specific required object. Besides, kitting policy saves the space that necessary for material storing at assembly lines since the only necessary parts that support the assembly of one object are presented at a time. The next step is to set objectives and overall project plan.

4.4.2 The setting of objectives and overall project plan

The objectives indicate the questions to be answered by simulation. The project plan should include all the required information that will be used in doing the intended study. The plan should include the required time for different stages of the study. The typical project objectives may involve the following (Chung, 2003):

- **Performance-Related Operating Policies:** The project objectives in this category are related to how to utilize existing resources. Another objective also could involve the layout of the process, and this means to determine the best alternative among many different configurations.
- **Performance-Related Resources Policies:** Objectives of this category involve different alternatives for resource distribution before selecting the best one. Manufacturing applications also could be included in this category. Here the objectives would be the type and number of manufacturing equipment that should be utilized by a particular system.
- **Equipment Capability Evaluation:** The objective of the simulation model of this category involves the evaluation process of proposed new equipment regarding its capability. Without

simulation, it is difficult to determine that the performance of the equipment will be the same as the actual one, as claimed.

- **Cost-Related Resources Policies:** Objectives in this category focus on reducing cost while maintaining the performance at a given level decided by decision-makers. In other words, the goal is to indicate the exact number of resources that are required to keep the system performance at an acceptable level.

As mentioned in the introduction section, the main objective is to design a new material handling system and then indicate the required number of AGVs before minimizing them. Thus, this thesis fills in the category of resource distribution. The next step is data collection and data analysis.

4.4.3 Data collection and data analysis

Data collection is one of the main steps in performing research. It is the actual commence that logically, every researcher must do to enable him or her to conduct the research. Data can be either quantitative or qualitative. The quantitative data is numeric data that deals with numbers, whereas the qualitative data is all other types of data such as words and figures. A data generation method is the means used to produce empirical data or evidence. The four main types of data generation can be ordered as follows: interviews, observations, questionnaires, and documents. For the project, three techniques are appropriate to comply based on the problem definition; they are interviews, observations, and documents. Each one of the three is discussed in detail to show how they are related to this thesis project (Oates, 2005).

- **Interviews:** Interviews are planned conversations prepared by the researcher, and they are not covered, this means that the research is not asked to hide his or her identity and try to act as a spy to obtain the required data. Interviews are proper for this project because they give detailed information about the case under study by meeting different people in the company and asking them about the subject of interest. The gathered data can then be analyzed to extract the necessary information. Besides, they are suitable to gain information that cannot be obtained through questionnaires because, in questionnaires, interviewees may not trust a person who they never met before.

  The flexibility to choose the appropriate person for a set of questions also makes interviews suitable for this project. It will be appropriate to conduct interviews with the company representatives about the validity of the designed simulation model and get some feedback.

Semi-structured interviews are what is going to be conducted because they enable to change the order of questions depending on the flow of conversation. Thus, production manager, vehicle drivers are mainly the persons of interest; and questions about production rates and the number of shifts, for instance, are the crucial questions regardless of the order. Some questions that have been asked during different interviews could be summarized as follows:

- How many rounds run the vehicles per hour?
- What is the demand for each type of kits per day?
- What is the time of loading and unloading times for the different types of Kits?
- What is the speed of the transportation system that is used to handle material into assembly lines?

The significant answers were summarized as follows:

- The demand for each type of kits per day was given.
- The number of cycles or rounds was calculated by analyzing the demand (throughput) of the different lines.
- The loading and unloading time for plastic boxes is 20 seconds.
- The loading and unloading time for pallets is 40 seconds.
- The speed of the transportation system is 7 km/h.

Documents are another way to generate data, and it is presented in the next paragraph.

- **Documents:** Basically, there are two types of documents that can be considered as a data generation method. The first type is researcher-generated documents, and they are put together for the research purpose. On the other hand, formed documents which represent the second type, are existing documents, and this type is suited to the project. Publications are formed documents that unavoidably should be used in any research project because the first part of any thesis or dissertation is the literature review about the subject of interest. Besides, the company documents could also be valuable resources of data like production plans, material inventory levels, demands, and throughput. Such information can be obtained in collaboration with the company supervisor before analyzing it.

For data analysis, interviews and observations data can be analyzed using quantitative analysis. However, documents can have both quantitative and qualitative analysis. They are both explained in the following sections:

- **Quantitative data:** Principally deal with numbers and Figures so they will be associated with interviews and observations as they are used in this thesis to collect numeric data. Tables, for instance, are one of many possible ways to analyze the collected data. This means that representing different values of one measured variable or factor can be best done using tables. For instance, the loading and unloading time, which is the time of loading the material from the material preparation area and unloading time of material in front of each production line, can be represented in tables. Quantitative data is used to decide the optimal length of input and output conveyors as well as the total lead time of the production process, for example, and both can be analyzed using tables.

  Moreover, it is significant to know the current capacity of each buffer to optimize it and obtain the so-called 'lean buffer,' and that will be intrinsic in deciding the required vehicles for material delivery. Some statistical measurements like the mean can be used to analyze the data and obtain the acceptable standard deviation, for instance.

  Furthermore, the processing time of each assembly line is collected in order to determine the minimum material safety storage time in case of any abnormality may happen. Statistical distributions such as triangular and normal distributions can be helpful to get more information about the disturbances and variation in the system and decide the mentioned number of vehicles accurately.

- **Qualitative data** In contrast to quantitative data, it deals with non-numeric data like images, sounds, texts, and more. For documents, apart from the quantitative side, including numeric data, qualitative data can be used to extract other embedded information. Minutes of meetings, quality plans, and production plans can be analyzed qualitatively, and this eases the way of how the process should go and which approach would be compatible with the company procedures and the aim of the thesis.

4.4.3.1 Case study data collection

The data collection is one of the most challenging steps in a simulation project since high-quality data is necessary to perform an accurate representation of a real system (Freivalds and Niebel, 2009).

In this study, the data was collected in coordination with the company's responsible people, and the historical records and interviews were used to obtain the necessary data. The primary data were the daily demand of all kits, the hourly throughput, and the line storage of line-side buffers. After gathering the required data, the analysis process was performed, and it represented in different tables and charts.

The following tables and figures represent the collected data. The complete figures for each data type are presented in **Appendix 3**. **Table 1**, shows the variants of the first family of products that are assembled on this line.

Line Number	A	
Variant or Kit Number	A 1	A 2
Demand/Day (Kits)	180.32	180.32
Throughput per Hour (Kits)	12.88	12.88
Line Storage (Kits)	25.76	25.76
Total Number of Kits per Day	360.64	

Table 1. Line A data

The daily demand of each variant is the same, and it equals to 180.32 kits per day. The reason for equality between the two variants is that one kit of each type is needed to form one product. The throughput is calculated based on the daily demand and the adequate production horizon, which equals to 14 hours. The maximum number of kits stored in different line storages is agreed to be equal to two-hours production. Finally, the total number of kits per day of all variants equals 360.64 kits. **Figure 9**, shows a representation of line A data.

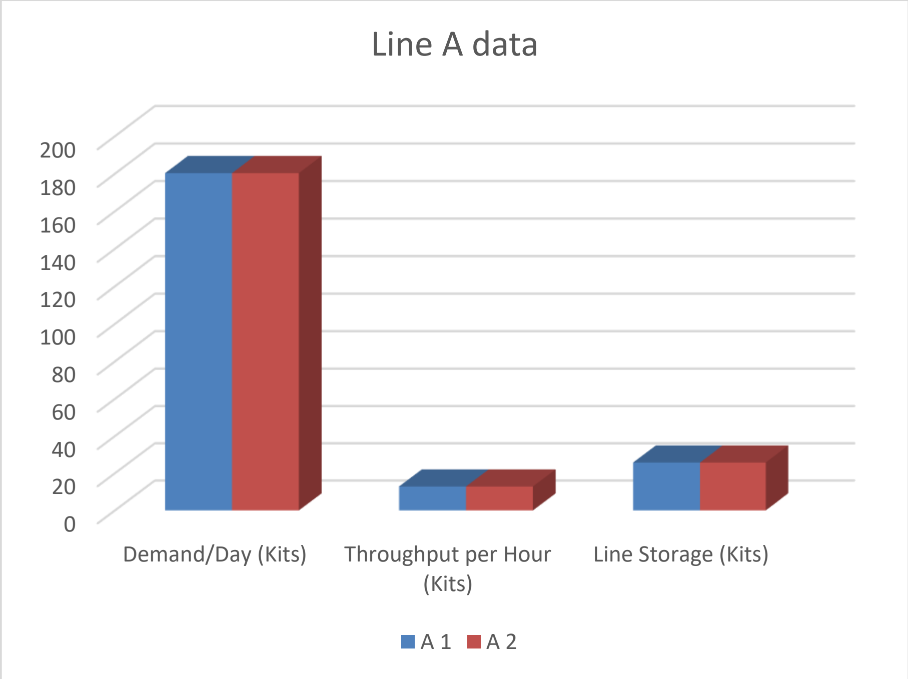


Figure 9. Line A data

The second, the third, and the fourth families of products are shown in Table 2.

Line Number	B								
Variant or Kit Number	B 1-1	B 1-2	B 1-3	B 2-1	B 2-2	B 2-3	B 3-1	B 3-2	B 3-3
Demand/Day (Kits)	99.5	99.5	99.5	58.5	58.5	58.52	64.4	64.4	64.4
Throughput per Hour (Kits)	7.11	7.11	7.11	4.18	4.18	4.18	4.6	4.6	4.6
Line Storage (Kits)	14.22	14.22	14.22	8.36	8.36	8.36	9.2	9.2	9.2
Total Number of Kits per Day	667.38								

Table 2. Line B data

Thus, three different families of products are assembled, and as it could be seen that each class consists of three integrated variants that form one product. The first three variants (B 1-1, B 1-2, B 1-3) forms the second family of products. The third family of products is produced by assembling variants (B 2-1, B 2-2, B 2-3). The last three variants (B 3-1, B 3-2, B 3-3) forms the fourth family of products. The daily demand for each class is different, and this means that the capacities of line storages at different assembly lines will be various also. The total number of kits per day equals 667.38 kits. Figure 10, shows a representation of line B data.

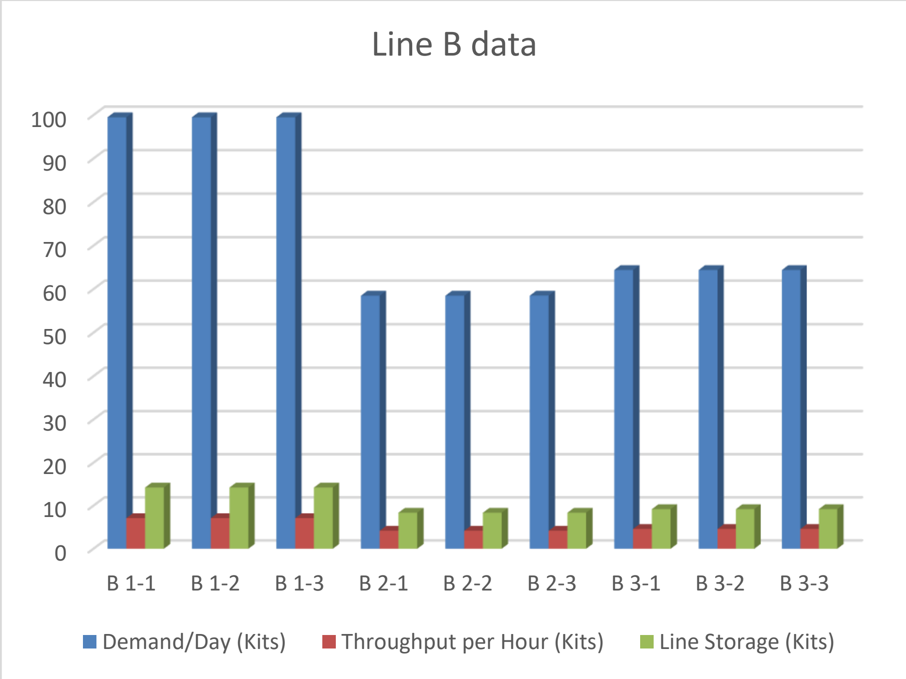


Figure 10. Line B data

The fifth and the sixth families of products, which are assembled at this line, are shown in Table 3.

Line Number	C			
Variant or Kit Number	C 1-1	C 1-2	C 2-1	C 2-2
Demand/Day (Kits)	40.32	40.32	13.02	13.02
Throughput per Hour (Kits)	2.88	2.88	0.93	0.93
Line Storage (Kits)	5.76	5.76	1.86	1.86
Total Number of Kits per Day	106.68			

Table 3. Line C data

Variants (C 1-1, C 1-2) composes the fifth family of products, and variants (C 2-1, C 2-2) forms the sixth family of products. The daily demand of the fifth and the sixth family of products is 40.32 kits and 13.02 kits, respectively. Line storage of the fifth family of products is 5.76 kits, and for the sixth family of products is 1.86 kits. The total number of kits per day is 106.68 kits. Figure 11, shows a representation of line C data.

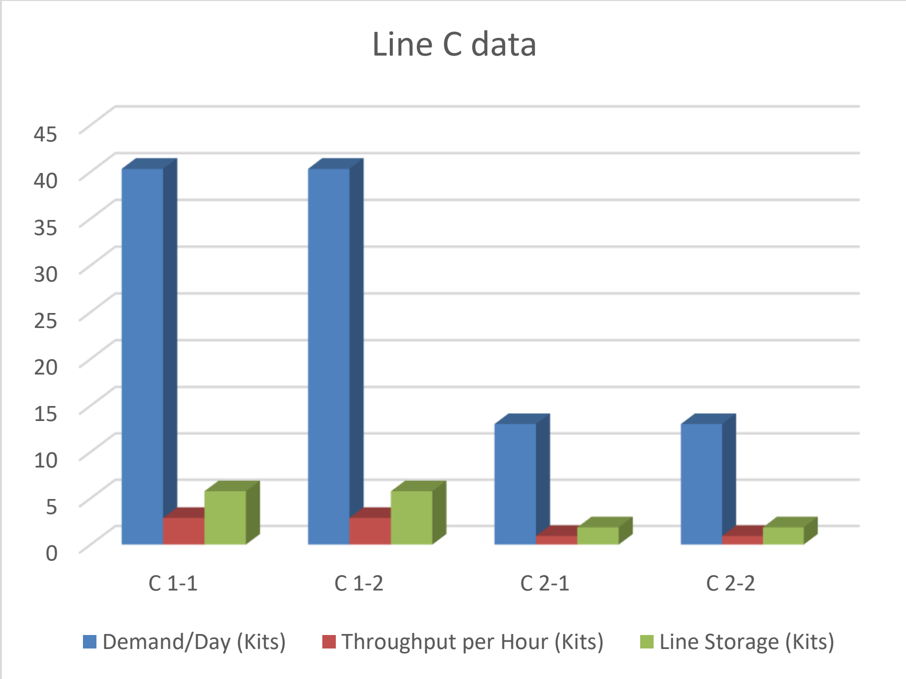


Figure 11. Line C data

Variants of the seventh and eighth families, which are assembled at this line, are shown in **Table 4**.

Line Number	D			
Variant or Kit Number	D 1-1	D 1-2	D 2-1	D 2-2
Demand/Day (Kits)	12.32	12.32	3.92	3.92
Throughput per Hour (Kits)	0.88	0.88	0.28	0.28
Line Storage (Kits)	1.76	1.76	0.56	0.56
Total Number of Kits per Day	32.48			

Table 4. Line D data

Variants (D 1-1, D 1-2) composes the seventh family of products, and variants (D 2-1, D 2-2) forms the last products' family. At this line, the lowest number of products is produced since the demand for those product's families is not so high as in the other families of products. The total number of kits per day is 32.48 kits. **Figure 12**, shows a representation of line D data.

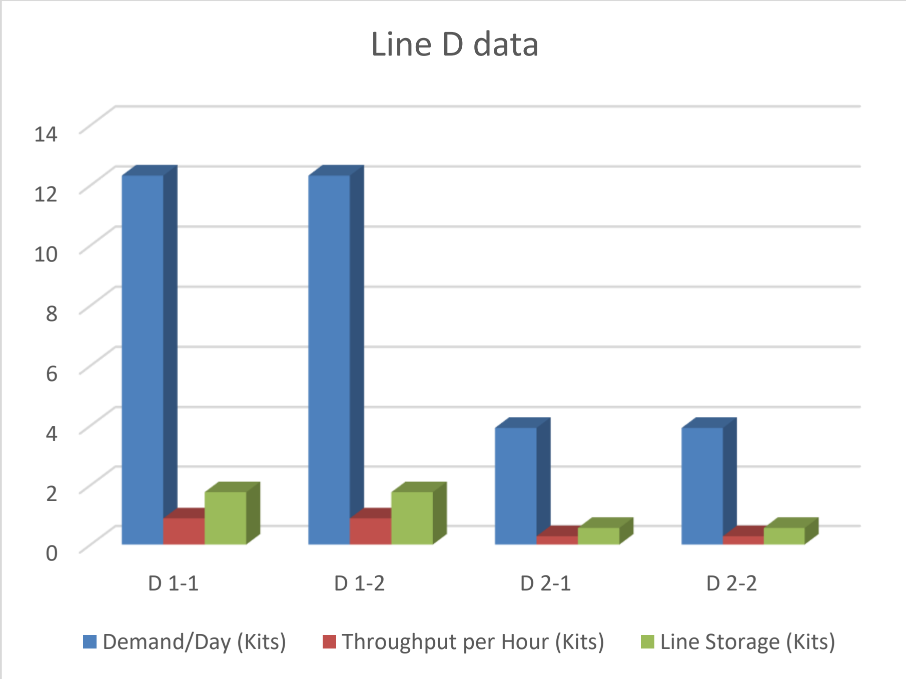


Figure 12. Line D data

The total number of kits per day of each assembly line is presented in the following figure, Figure 13.

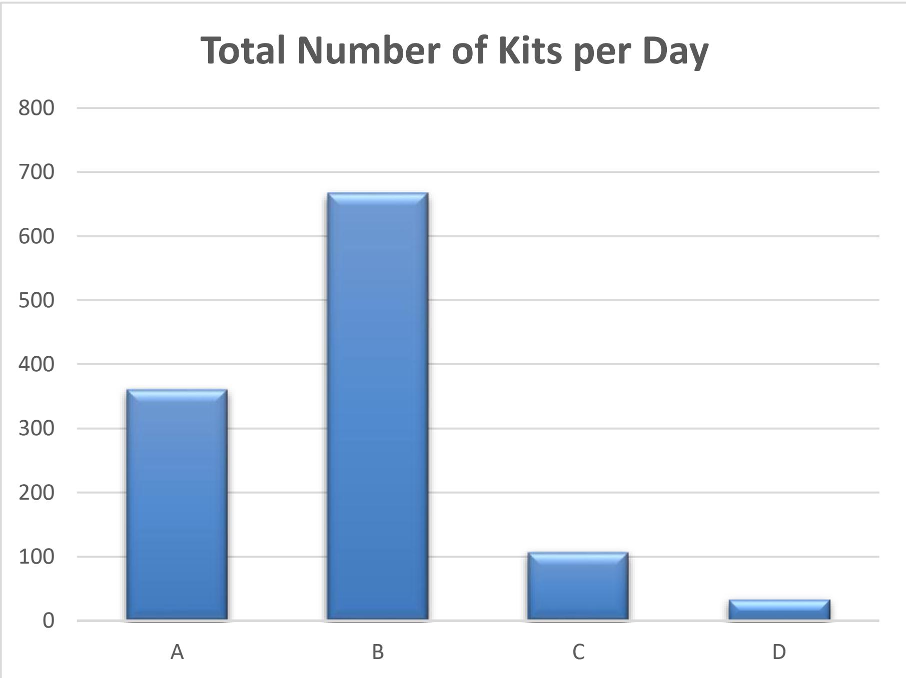


Figure 13. Total number of kits per day

As shown in figure 13, the maximum value of the daily demand for kits is located at line B since three different families of products are assembled at this line.

4.4.4 Model conceptualization

The process of model construction needs a thorough understanding of the system required to build the simulation model. Model conceptualization is one of two" key steps" to perform a suitable model in order to obtain accurate results. "The art of modeling is enhanced by an ability to abstract the essential features of a problem, to select and modify basic assumptions that characterize the system, and then enrich and elaborate the model unit a useful approximation results" (Banks et al., 2005).

4.4.4.1 Material preparation area

Material preparation area (MPA), is the area where parts of the same product are put together and stored in their kits (plastic boxes or pallets) to move to the production lines. Kits are stored in the kits storage and prepared to be filled with different parts. Empty kits that AGVs unload on input conveyors are stored in the kit's storage area. When the required amount of kits is placed on the output conveyors, one AGV comes to load a specific number of kits depending on its capacity and the demand. At assembly lines, kits are emptied then loaded on AGVs to move them to input conveyors (**Figure 14**).

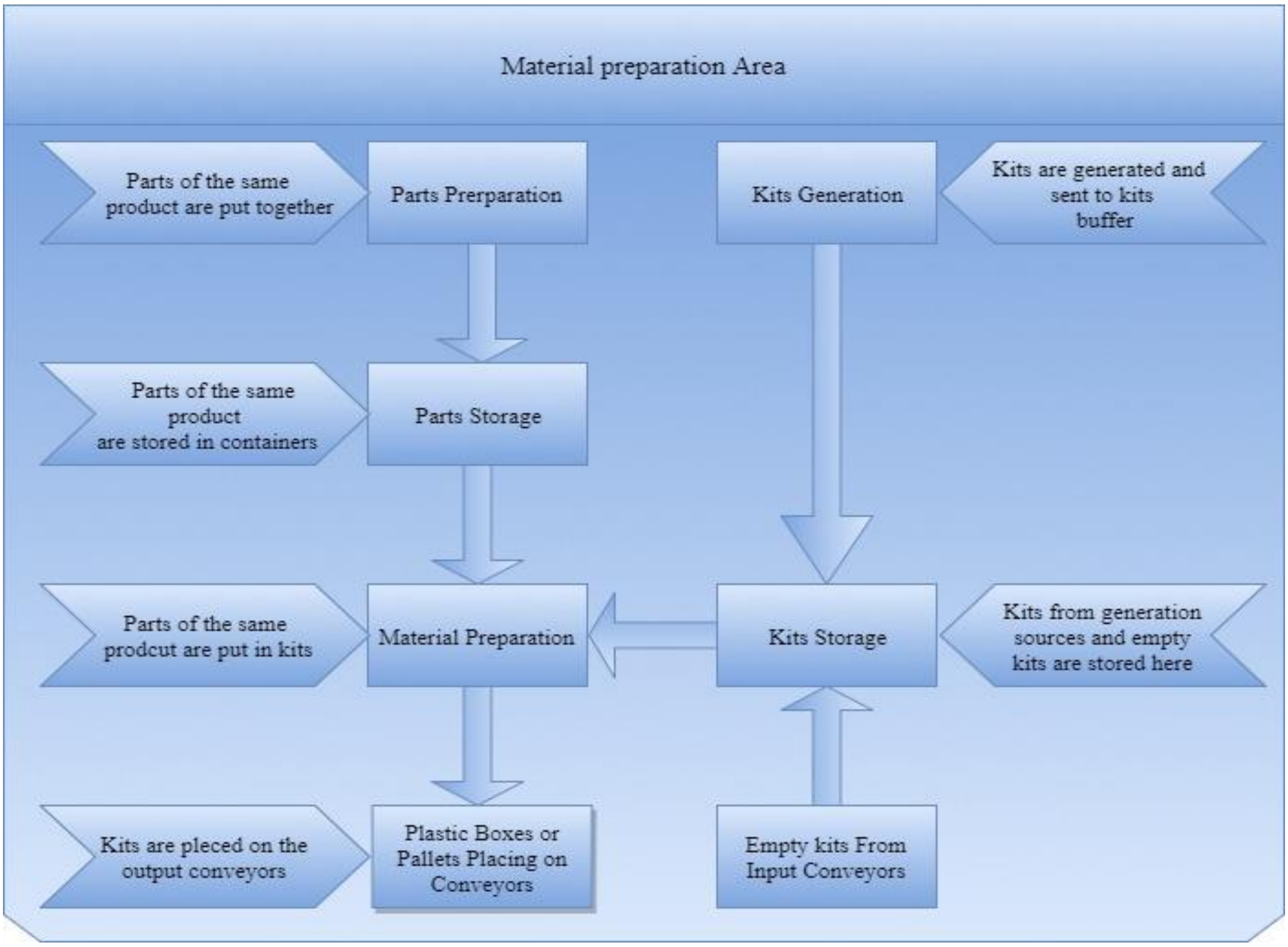


Figure 14. The conceptual model of material preparation area

It is essential to mention that the material preparation area is not included in the scope of this project, then it is just modeled as a black box with inputs and outputs. The next area is the material handling area.

4.4.4.2 Material handling area

Material Handling Area (MHA), is the area where AGVs handle the kits prepared at the MPA to assembly lines. AGVs load the kits regarding its capacities and the required number of kits during each cycle, and then they transport them to the assembly lines following predetermined paths. This process is represented in **Figure 15**.

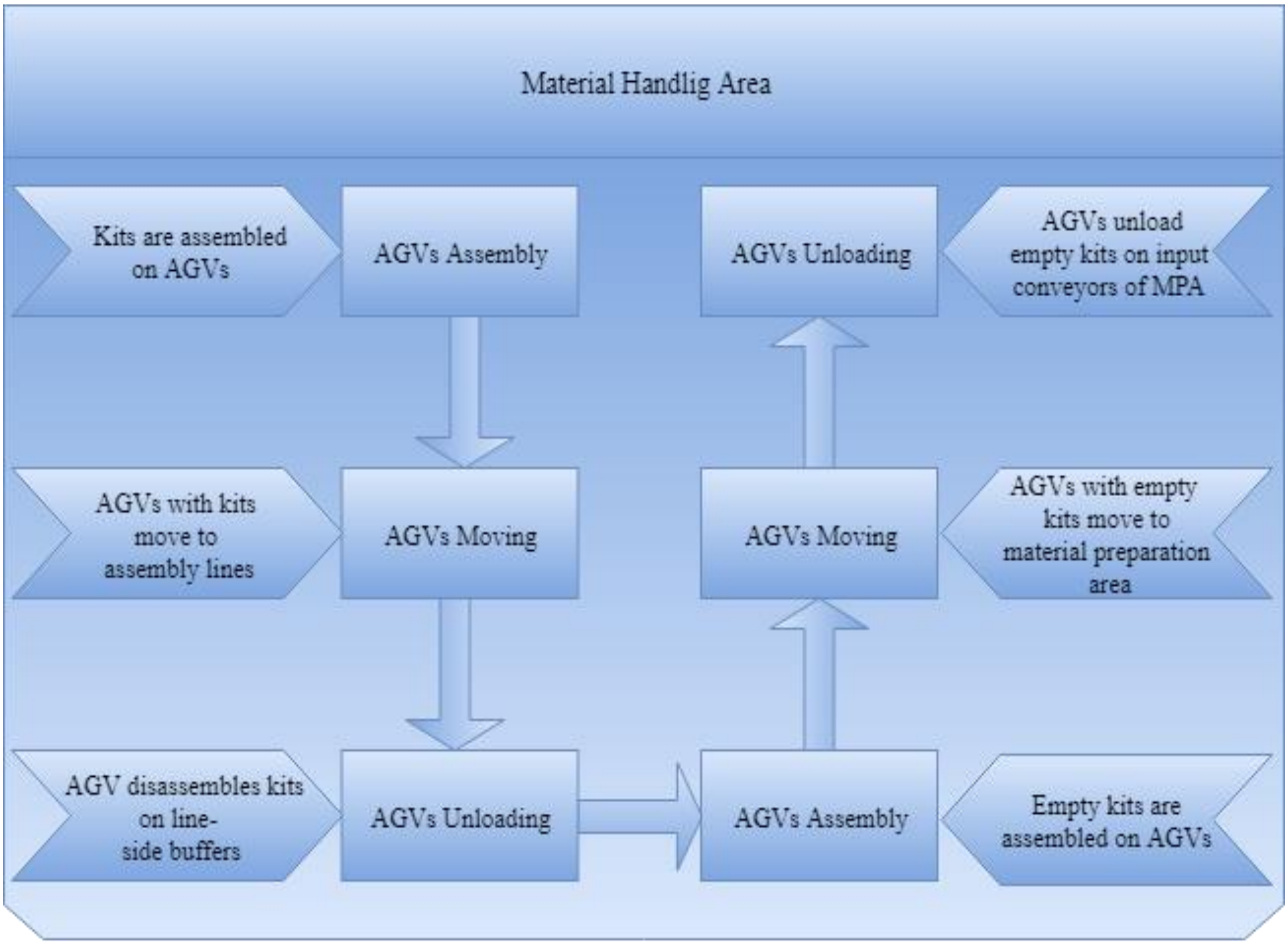


Figure 15. The conceptual model of the material handling area

At unloading stations, AGVs unload the kits in the line-side buffers and load the empty boxes that were waiting to be transported back from previous cycles. Afterward, AGVs transport the empty boxes following predetermined paths towards the input conveyors of the MPA to unload them and start a new cycle. The transportation time was calculated based on the distance between the material preparation area and assembly lines on one hand. On the other hand, the speed of AGVs was supposed to be 7 km/h, and with the actual distance between assembly lines and MPA input/output conveyors, the transportation time was calculated. The last area is the assembly area, explained in the following section.

4.4.4.3 Assembly area

The assembly area is compound by the production lines, where kits are stored in line-side buffers. The following figure, **Figure 16**, illustrates this area.

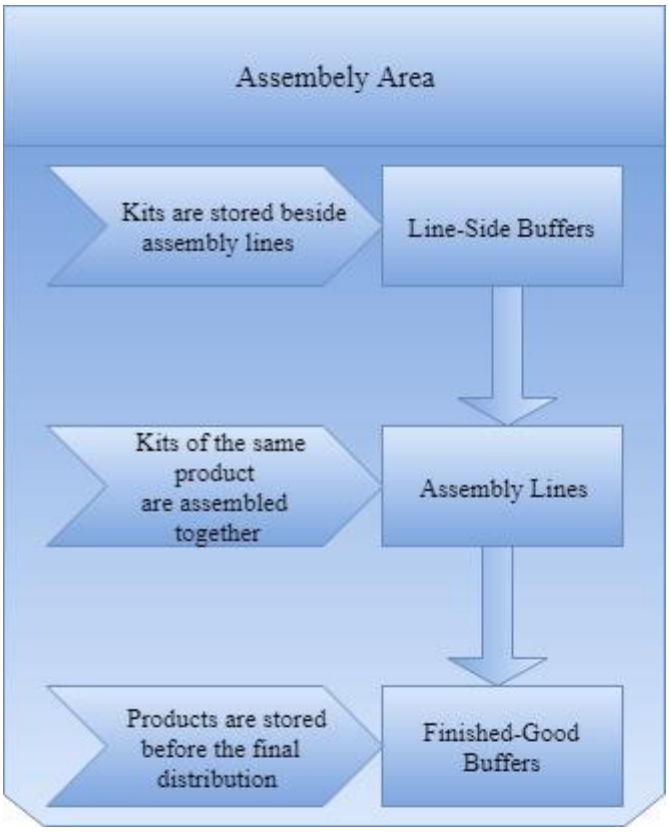


Figure 16. The conceptual model of the assembly area

Afterward, parts of the same product being assembled and being kept in finished-good buffers before the final distribution. The assembly time for each type of product is calculated based on the daily demand, which is obtained in the data analysis previously performed. The combination of the three areas represents the entire conceptual model that is illustrated in the following figure, **Figure 17**, on the next page.

The next section is the model translation. In this section, a brief introduction about the simulation software tool is given, and the process of simulation model construction is presented in detail. This process includes introducing the different model’s variants that form the final products as well as the different project flows. Additionally, the various properties of the input and output conveyors, plastic boxes, and pallets are presented as well. Besides, the transportation times between the material preparation area and different production lines are calculated and presented. Furthermore, the mechanism of material flow control is introduced. Finally, the entire simulation model is demonstrated at the end of this section.

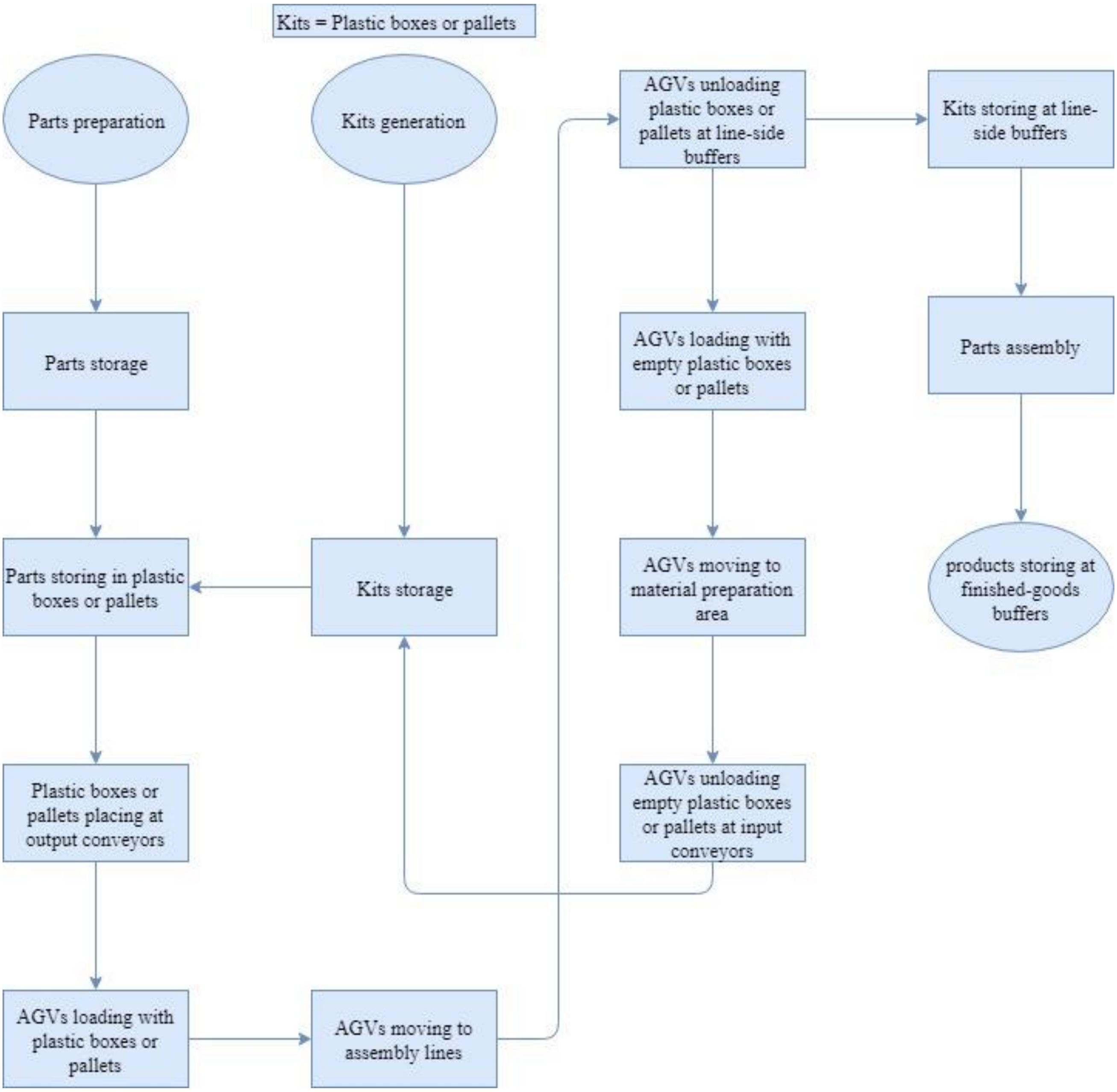


Figure 17. The entire conceptual model

4.4.5 Model translation

After analyzing the collected data and designing the conceptual model, it is possible to start the process of model translation. In the beginning, the simulation software tool selected for this project was the Facts Analyzer, which has been developed by the University of Skövde. The opted software tool is appropriate for this kind of study because it has remarkably advanced options to deal with the discrete-event simulation problems that contain optimization processes. The interface of the Fact Analyzer is presented in the following figure, **Figure 18**.

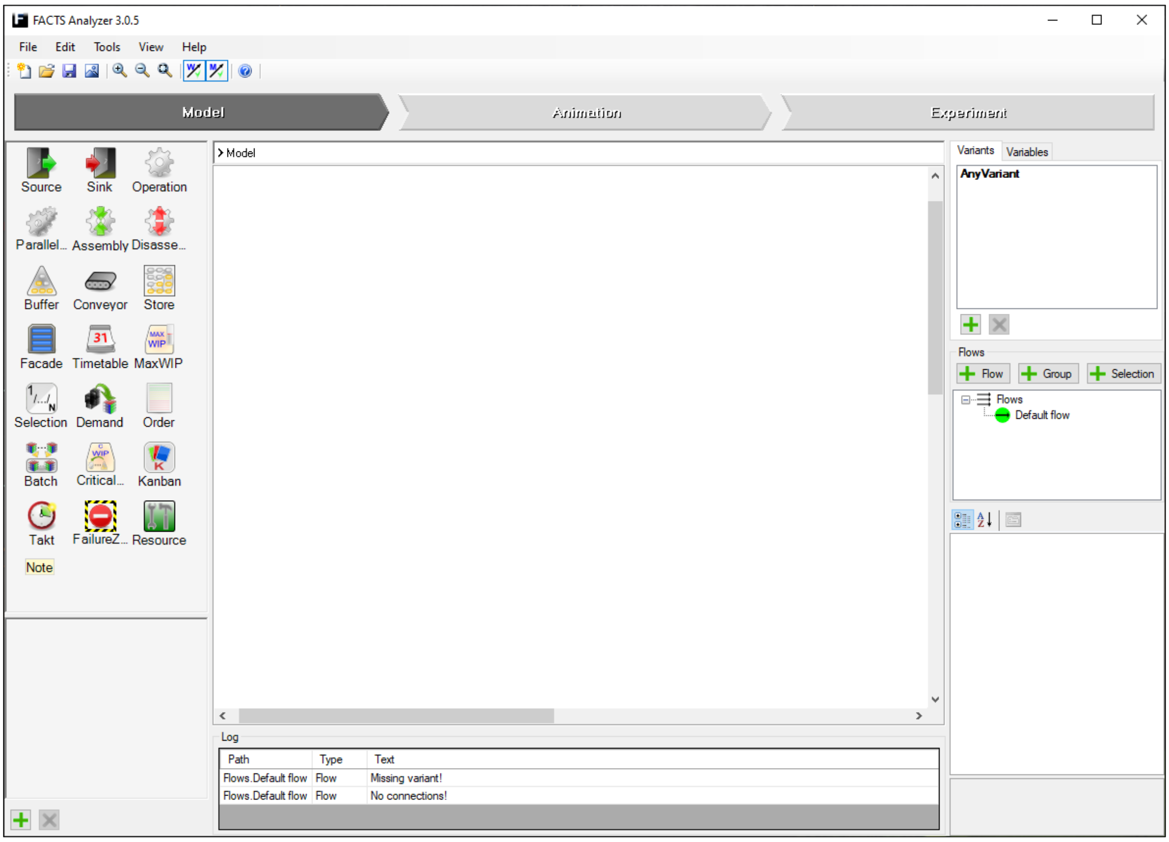


Figure 18. Facts Analyzer interface (Ng et al., 2007)

As indicated in Figure 18, the software consists of three primary tabs, and the first one is the model tab where the simulation model is designed. It includes different objects and variants that are required to build the model. The second tab is the Animation, where the model is run to observe its behavior and make some modifications if required. The last tab is for the experiment, where the model is run under specific numbers of times, including warm-up and simulation horizon to obtain outputs of the model (Ng et al., 2007). The following three sections explain the process of simulation model construction. The first step takes place in MPA, where the variants of the model are inserted.

4.4.5.1 Material preparation area

The simulation model consists of three fundamental areas, which are the material preparation area, material handling area, and assembly area. Variants (parts) filled in kits and delivered to assembly lines. The usage of variants is to model different entities that move between different objects in the model. They can be used to represent material flows, to model resources such as AGVs, pallets, workers. The names of assembly lines (production lines) are line A and line B for plastic boxes; line C and line D for pallets. Line A produces one family of products, and line B produces three families of products, line C and line D produce two families of products. The lean 5S tool is applied here, where each kit has its particular place in MPA. By using Facts Analyzer software, the first step is to enter the different variants that form the different families of products. The next figure, **Figure 19**, shows the insertion of a new variant.

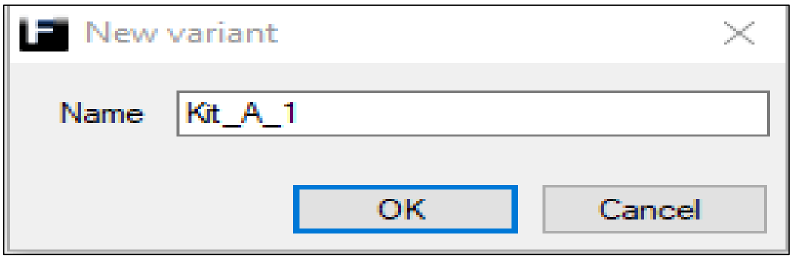


Figure 19. New variant insertion

The next table, **Table 5**, shows the variants used to form the final products.

Line	A		B			C		D	
Variants	Kit A-1	Kit A-2	Kit-B-1-1	Kit-B-2-1	Kit-B-3-1	Kit-C-1-1	Kit-C-2-1	Kit-D-1-1	Kit-D-2-1
			Kit-B-1-2	Kit-B-2-2	Kit-B-3-2	Kit-C-1-2	Kit-C-2-2	Kit-D-1-2	Kit-D-2-2
			Kit-B-1-3	Kit-B-2-3	Kit-B-3-3				

Table 5. Variants of assembly lines

As shown in Table 5, two variants used to build the first family of products in line A. The second line needs nine variants to build different types of products families. The last two lines assemble eight variants to produce several families of products. The letters and numbers in each variant type differentiate it from other variants, for instance, (Kit-B-1-1) means the following:

The letter B represents the line it belongs, and the first number refers to the product family it belongs, whereas the second number refers to which kit it is, if the 1st one, or the 2nd one. Usually, two kits are necessary to build one product, except for the second line, where three kits are required to produce one product.

In the simulation model, the families of products follow different flows along the way to the final-goods buffers. These flows act for different ways that model's objects and entities follow to reach their final destinations. The assembly lines assemble nineteen different variants that represent the final products; Thus, nineteen flows exemplify all families of products.

Additionally, another two flows represent the two types of AGVs used in this project besides one flow for the two types of containers, which are plastic boxes and pallets. Figure 20, illustrates the different flows in this project and the deterministic variants of each flow.

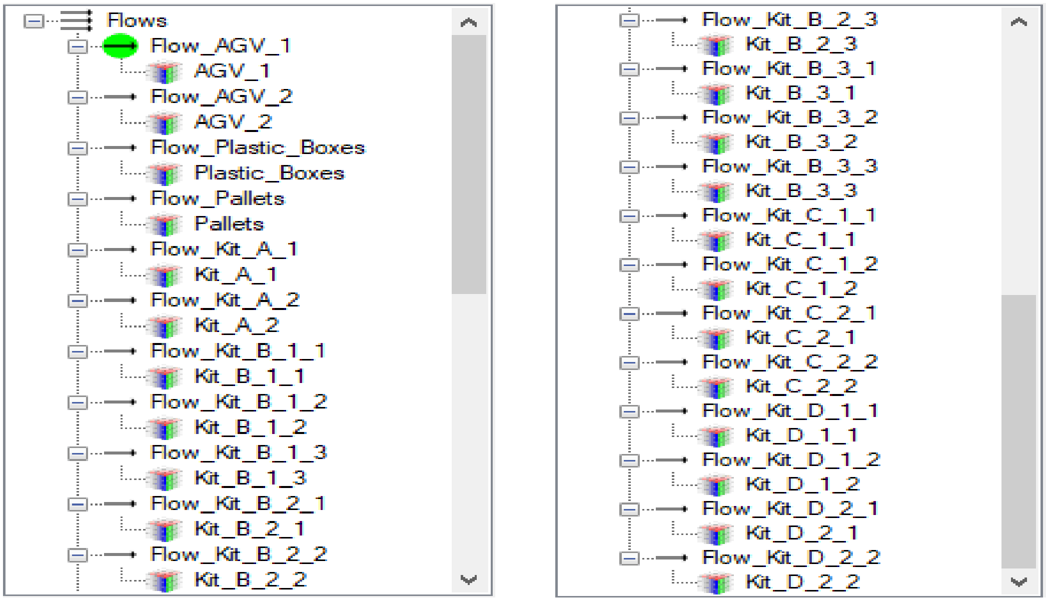


Figure 20. Flows of the model

The material preparation area contains different parts to be assembled and kits that include the corresponding parts. The first step in the simulation process is to enter all variants that will be assembled in a particular way to form the final product. Final products are formed by using nineteen variants inside kits, and they travel to assembly lines on AGVs. As mentioned above, four additional variants added to represent the selected type of vehicles, which are AGVs and the containers or kits that include variants of different product families (Figure 21).

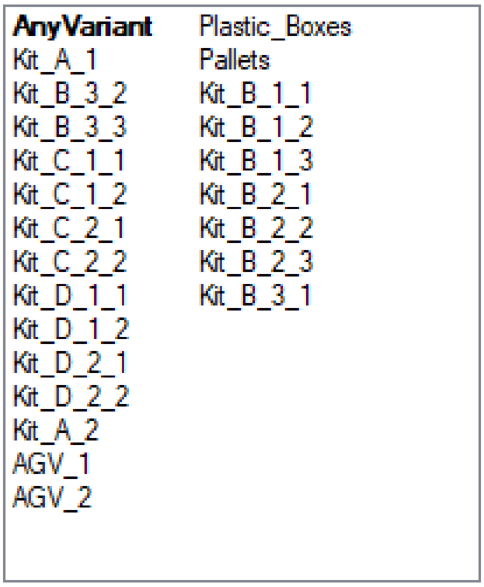


Figure 21. Variants of the model

As shown in Figure 21, "AGV-1" and "AGV-2" represent the transportation system, and "Plastic Boxes" and "Pallets" represent the type of container. In the simulation model, the variants mentioned above are generated at the MPA according to the demand of different production lines. Variants generation act for the material supply to the factory in reality.

Once the variants were introduced in the simulation model, it was time to model the generation of kits. All lines except line B need two kits to produce one product, and line B needs three kits. Thus, parts of a particular product putting in kits and being stored in the material preparation area.

For a controlling purpose in the model, variants for the same products family are assembled and put in kits before being stored in their places, and the assembly time is zero because the purpose here is just for control. This step is significant in order to avoid the problem of shortage or blocking. In other words, the variants are generated cyclically and sent to the following item in the same manner before being kept in the MPA or supermarket. Therefore, kits of the same family of products should be stored and handled together during the same cycle. In the simulation model, AGVs unload variants at line-side buffers that keep them according to their limit proportions, and when all variants are presented, the variants of the highest percentage will have the priority in the next cycles. Thus, for the reason that variants are supplied cyclically, it is not guaranteed to have the necessary variants at the right time. This leads to a shortage problem since the demand for each assembly line is different. For a reason explained in the previous paragraph, the generation of variants of the same family of products will be done using separate sources; then, they will be assembled before sending them to the material preparation area. The following figure, Figure 22, shows an example of kits assembly of the same product.

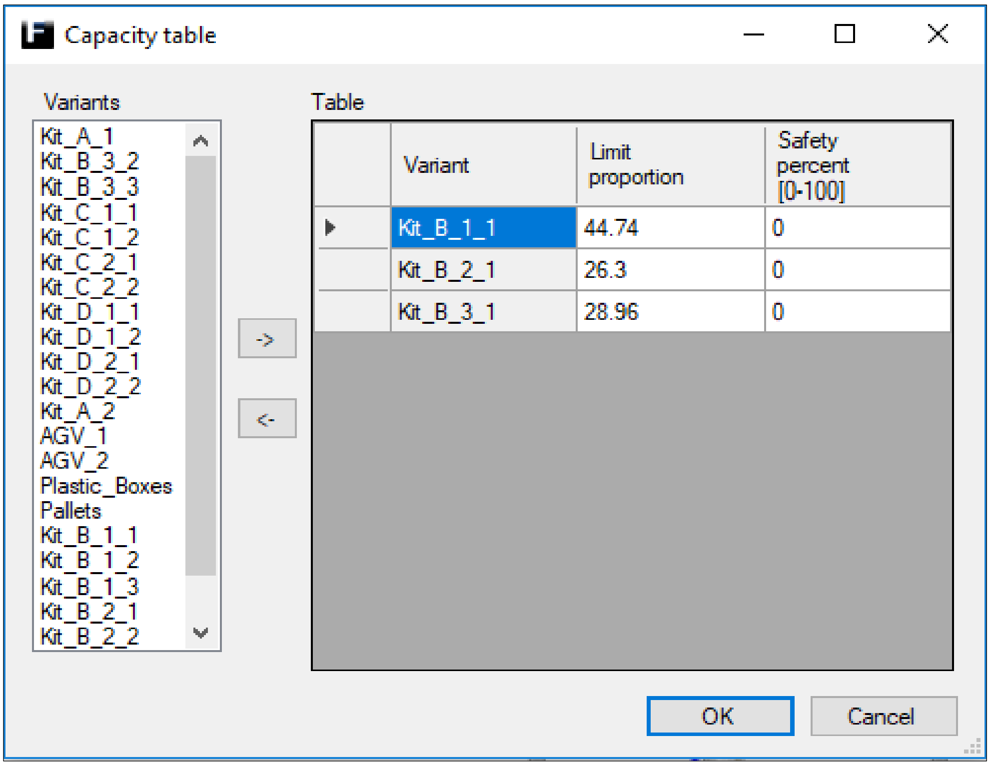


Figure 22. The capacity table of line B and the corresponded limit proportions

As shown in the previous figure, the kitting process of one product kind on line B takes place. In this process, each variant needs three kits, and there are three product variants produced in that line, then nine assembly tables are required. In the same figure can be appreciated the three types of product B along with their manufacturing proportions. The material is grouped and stored in MPA regarding the kitting policy that has been explained earlier. The capacity of the MPA is decided to be enough for one-day production for all kits that form all product kinds.

Now, all kits exist in their places in the MPA. After that, parts will be placed in kits in the pallets or plastic boxes. Line A, line B are for small-range products and line C, line D for mid-range products. After preparing all kits and arrange them in MPA, they are sent to conveyors before one AGV carry them to assembly lines. The initial length of conveyors is decided to be 10 meters supposing the sizes are European sizes of plastic boxes and pallets (0.6 x 0.4) meters and (1.2 x 0.8) meters, respectively. In the next figure, Figure 23, the chosen settings for all conveyors in this project are shown.

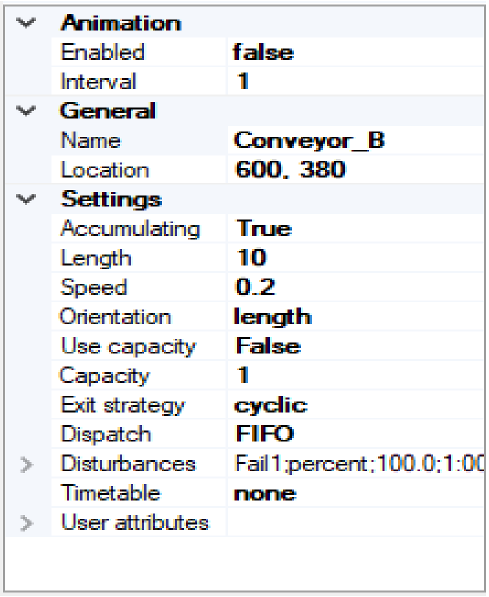


Figure 23. Settings of project's conveyors

Separated sources in the simulation model generate kits; then, they are sent to their predetermined flows in the MPA. The generation process of kits is limited to a specific number, and it is found that the best number is 60 for plastic boxes and 40 for pallets (Figure 24).

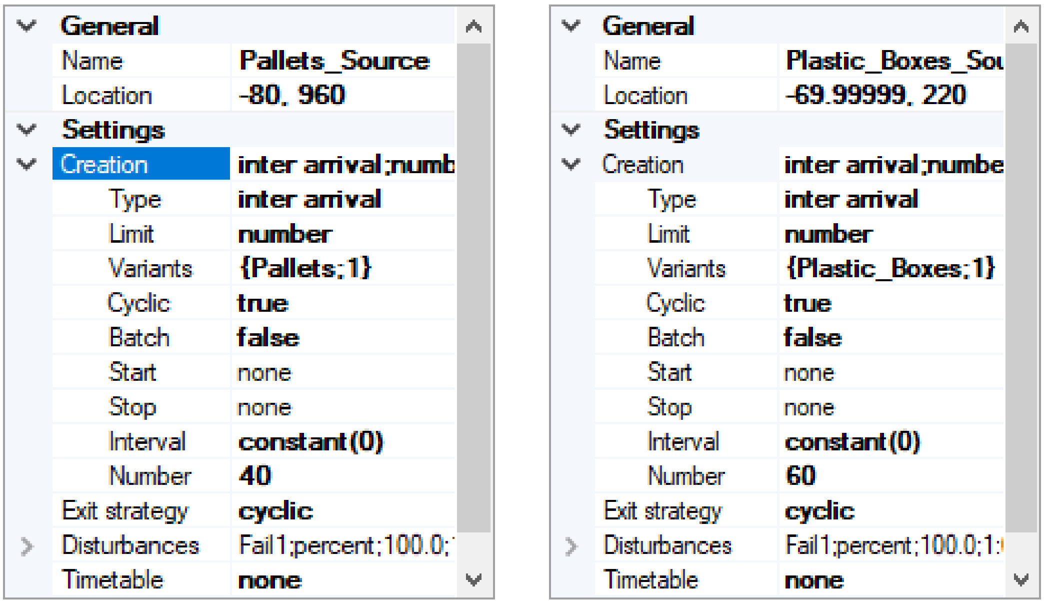


Figure 24. The best numbers of plastic boxes and pallets

After defining the model's variants and flows, the settings of conveyors, and the best numbers of different containers (kits), the next step of the model construction process is to illustrate the handling process, and this takes place in the material handling area.

4.4.5.2 Material handling area

Material handling area is the area in which vehicles are generated and sent to a garage located close to MPA, and from there, they move to conveyors that contain kits in order to handle them into assembly lines. Consequently, AGVs load kits with a capacity of plastic boxes equal to (6) and for pallets limits to (1). Thus, two types of AGVs assigned in this project. The first one will be called AGV_1, and this type is devoted to small-range products with a capacity of 6 boxes. In the simulation model, it is crucial to indicate the leading flow when the kits loading process happens. In other words, the entities of the simulation model have different streams, and at the moment of kits loading, the flow of AGVs has to be selected. It is possible to do that by choosing the assembly identity of AGVs. The following figure, Figure 25, illustrates the assembly process of plastic boxes on AGV_1 with a capacity of six kits and shows that the assembly identity was selected to be true for AGVs.

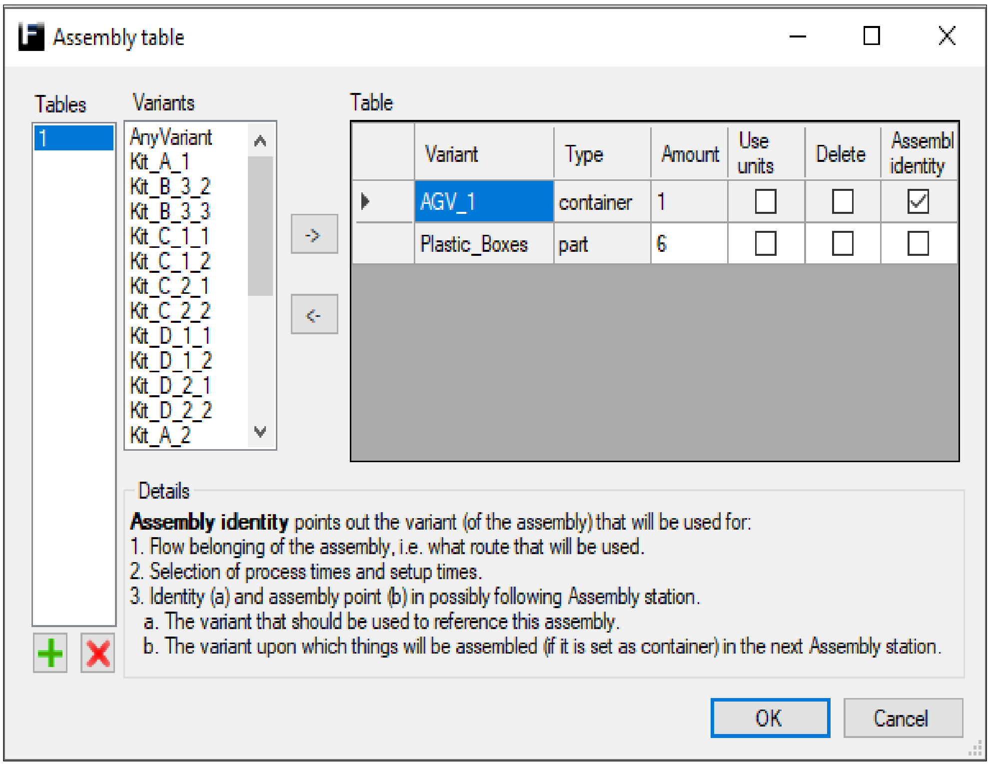


Figure 25. Assembly table of plastic boxes with AGV_1

On the other hand, AGV_2 is the second type, and it is devoted to mid-range kits with a capacity of 1 pallet. The following figure, Figure 26, shows the process of pallets assembly on AGV_2 with a capacity of one pallet.

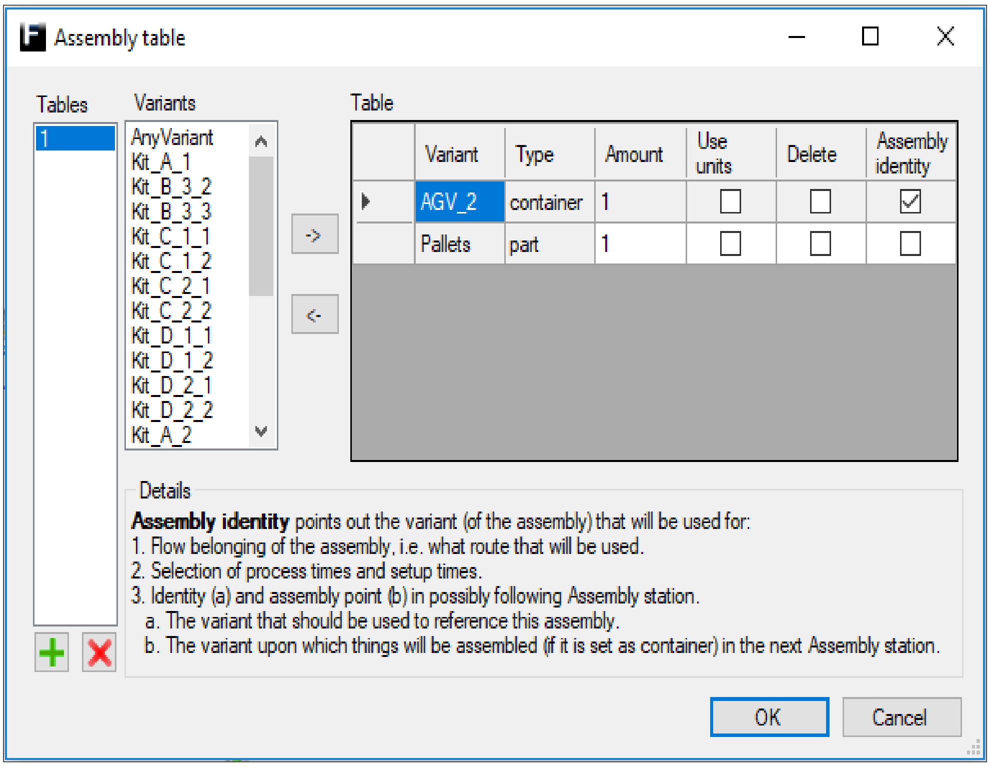


Figure 26. Assembly table of pallets with AGV_2

AGVs move to assembly lines after loading the particular number of kits that decided on the production lines. The triangular distribution was applied for transportation time, and it is calculated regarding the proposed layout. In more detail, the distance between the material preparation area and each assembly line is known, and the speed of AGVs has been proposed.

The transportation time of each line is known, and **Table 6** shows their values. The previous values were calculated based on the proposed layout of this main shop floor of this project that is represented in **Figure1**.

	Line A	Line B	Line C	Line D
Transportation Time (Sec)	26	20.5	15	9

Table 6. Transportation time till each assembly line

The previous numbers represent the minimum transportation time on triangular distribution. To make the model more realistic, the maximum magnitude of transportation time will be double, and the mode time could be calculated using the following formula:

$$\boldsymbol{Mode\ time = Minimum\ time + \frac{Minimum\ time}{4}}$$

Equation 6. Calculation of mode time

The AGVs continue to transport to line-side buffers, then AGVs unload the kits. The kits go to the assembly lines when needed to be assembled and formed final goods. For the empty kits (containers), they are loaded by AGVs and handled to the MPA again following the return lines, which have the same distance and transportation time. When AGVs reach the input conveyors of MPA, they unload kits and go to the starting point or the garage to start a new cycle, and kits are filled again with various parts. As parts reach line-side buffers, the final step of building the simulation model starts, and this occurs in the assembly area.

4.4.5.3 Assembly area

Assembly lines where parts coming in the form of kits to be assembled in order to form the final product. The kits are stored in the line-side buffers and prepared for Analyze according to the processing time f different assembly lines. That time is calculated regarding the daily demand that is determined and decided by the management. For assembly time modeling, a triangular distribution is assigned in order to add some variability to the model. The maximum and minimum times are assigned to be 10% of the mode time. In the results comparison section, it will be removed, and the reason is related to the accuracy purpose.

The effective horizon is decided to be 14 hours that represent the working hours of two shifts a day. Thus, the daily demand is divided by 14, and the result will be for one hour, which represents the throughput per hour. Then, 60 minutes is divided by the hourly throughput, and the resulted number will be the processing time for one product. Line-side buffers are designed to keep a two-hours of production, and it is asked to maintain a minimum of one-hour production. To achieve this desired level, the batch object is introduced to control the number of kits that should enter buffers of assembly lines. In more detail, the capacity of assembly lines' buffers that contain parts to be gathered is divided among variants according to demand for the different product families. Therefore, limit proportions are different, and the object which controls the process of material feeding is the batch object. The way of how the batch object connected is, the input comes from the line-side buffers that contain the safety percent of the buffers to be kept and the output connected to the processes that produce that necessary parts to maintain the safety percentages of each line-side buffers. The way that the batch object works in the simulation model could be explained simply by saying that the connection from the Batch object to an Operation ensures that the operation processes batches of the parts waiting at the stores located before them. The connection from a Store to the Batch object will make the Batch object bring safety stock shortages from this Store in order to give priority to the variants with the most considerable shortage. The capacity table of the line-side buffer of line B is shown in the next figure, **Figure 27**.

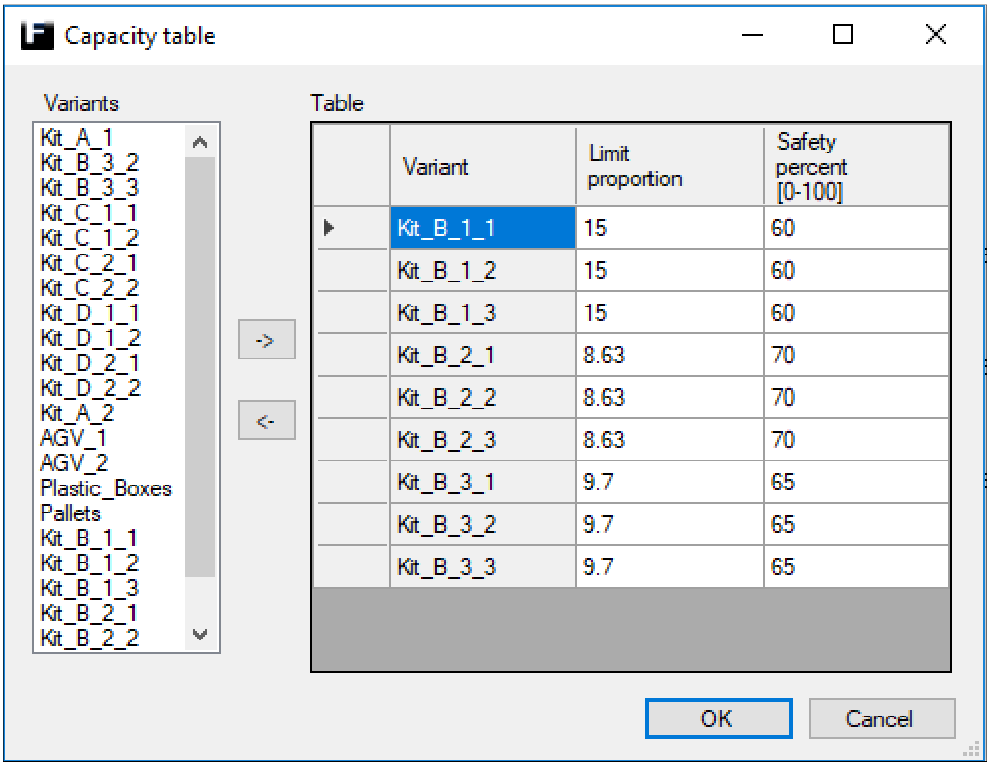


Figure 27. The capacity table of the line-side buffer of line B

The next figure, **Figure 28**, shows the first simulation model on the next page. This model will be referred to as the basic model, and the different designed scenarios will be compared to it.

The next section is the Verification and Validation. In this section, a comprehensive explanation for the process of model verification and validation is given. In the verification process, the variability study in which the model is evaluated is conducted, and some essential concepts such as T-distribution and confidence interval are presented. The variability study process consists of two significant steps; the first one is the replication analysis, and the second one is the steady-state analysis. In the replication analysis section, two fundamental approaches used to indicate the number of required replications are introduced. Then, the appropriate period to run the simulation model is determined in the section of steady-state analysis. Furthermore, the process of model validation is interpreted. Finally, the improved "what-if" scenarios and the second simulation model of the last scenario are presented at the end of this section.

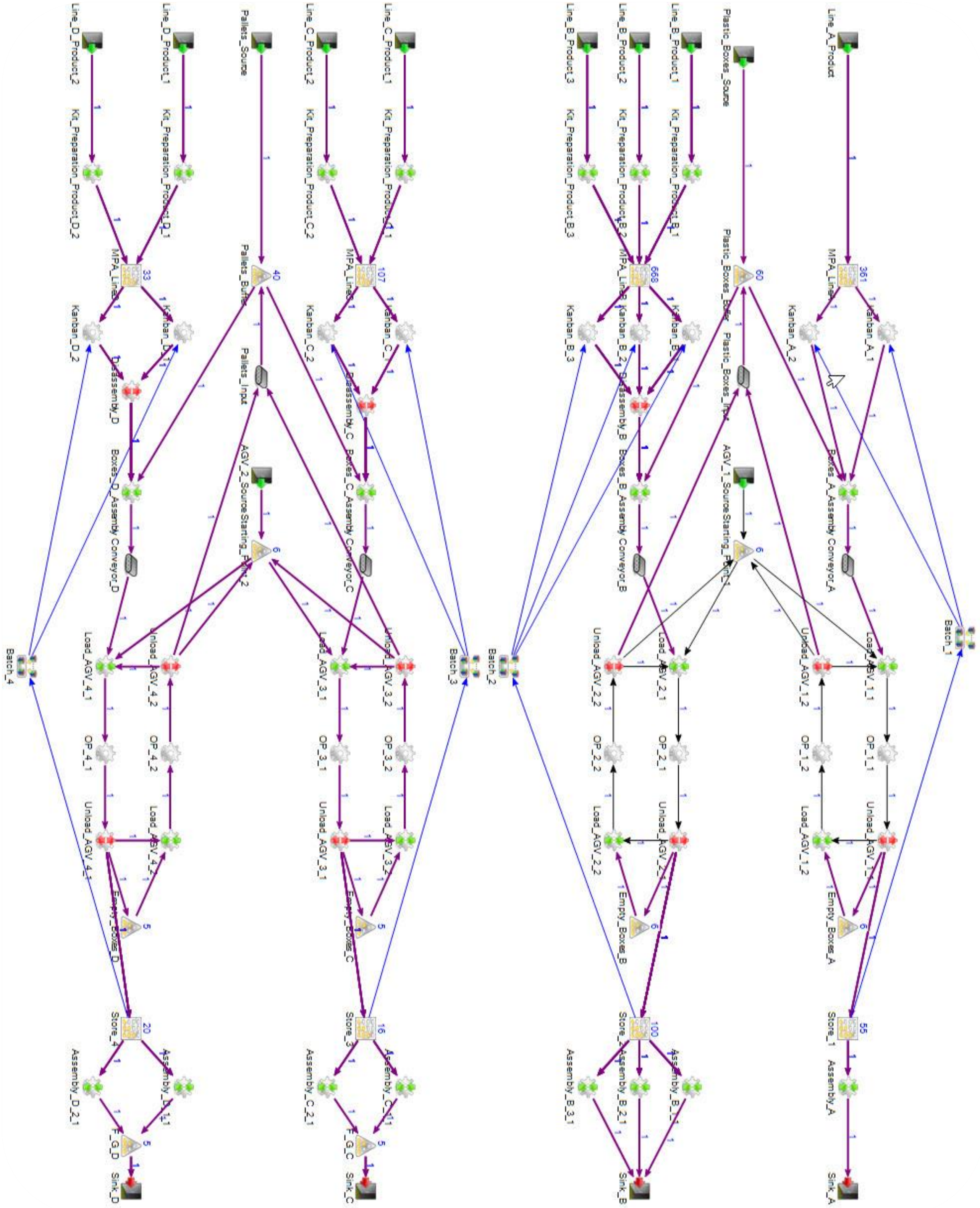


Figure 28. The basic simulation model

4.4.6 Verification and Validation

The simulation model is built, and the insight of how it behaves was obtained. The next step is to make sure that the model was built correctly, and it represents the real-world system, and this could be done by the verification and validation processes. They are explained here below.

4.4.6.1 Model verification

The verification process is a determination of whether the computer program by which the conceptual model has been translated is suitable or not for the study (Banks et al., 2005). It is to ensure that the computer program represents the system in the same way as the real one is. Every process in the modeling needs to be performed in the right way using the necessary staff only. The input parameters, logical structures, and the assumed data have to be correctly represented. In other words, verification is the process of ensuring that the simulation model has all the necessary components and that the model actually runs. In this project, every variant has been followed from the generation sources in the model along the way until the exit sources or "sinks." Besides, different flows were also observed to make sure that variants follow the exact way as in reality. Moreover, the total number of variants and kits have also been revised to assure an accurate representation of the system. After conducting the verification process, it is possible to proceed with the validation process.

4.4.6.2 Model validation

The validation process is the determination process of comparing the simulation model against the actual system behavior (Banks et al., 2005). Validation is to assure that the model reflects the core of the real-world system. During the validation process, the model was checked thoroughly, and several visits were done to the company to discuss it. The model was discussed with the company representatives such as project coordinator, simulation expert, production engineer. During Kaizen meetings, the results were presented, and feedbacks were noted to be implemented on the model. Then, the model was presented and discussed again step by step until the management was satisfied. By analyzing the results of the validation process, it could be said that the output results of the simulation model were identical with the real system in a good enough percentage. The throughput value gives a good indication of how much valid the model is since it represents the final product. Thus, it would be the chosen parameter to illustrates the outcomes of the validation process of this project. The following table, **Table 7**, shows the validation process for the basic model concerning the throughput, the most significant parameter.

	Real Data			Simulation Data			Difference (%)		
	Throughput (product/hour)								
Line 710	Var A-1			Var A-1			Var A-1		
	12.88			12.9			-0.15		
Line 711	Var B 1-1	Var B 2-1	Var B 3-1	Var B 1-1	Var B 2-1	Var B 3-1	Var B 1-1	Var B 2-1	Var B 3-1
	7.11	4.18	4.6	7.11	4.24	4.52	0%	-1.43	1.7
Line 712	Var C 1-1	Var C 2-1		Var C 1-1	Var C 2-1		Var C 1-1	Var C 2-1	
	2.88	0.93		2.88	0.93		0%	0%	
Line 713	Var D 1-1	Var D 2-1		Var D 1-1	Var D 2-1		Var D 1-1	Var D 2-1	
	0.88	0.28		0.88	0.28		0%	0%	

Table 7. The validation table of the basic model

The previous table demonstrates the real values of throughput for all variants on the one hand. On the other hand, it also shows the values that resulted after running the simulation model, specifying the throughput of all variants as well. The last column represents the difference between the results of the real data and simulated one; it is calculated as the following formula:

$$\boldsymbol{Difference = 100 - \frac{\overline{x}_{model} * 100}{\overline{x}_{real}}}$$

Equation 7.The formula of the difference between the real system and the simulation model

In this case, this difference was lower than 5% for the mean values; for this project, it was considered to be accurate enough. The obtained results from the simulation represent good enough real values. With these results, the validation of the model was performed. The next step is to conduct the variability study. In this study, two primary analyses are introduced, the first one is the replication analysis, and the second one is the steady-state analysis that is explained in the next two sections.

4.4.7 Variability study

The variability study is the process of model evaluation, and it is an essential step in the whole simulation study because it indicates the reliability of the designed model. Before going further in the explanation of the variability study, some definitions need to be illustrated.

- **T-distribution**

According to Senn and Richardson (1994), T-distribution is used instead of the normal distribution when the size of the sample is small. It is used in numerous statistical analyses, such as assessing the statistical significance of the difference between the two samples mean values and the construction of confidence intervals for the difference between two population mean values. The T-distribution is a group of distributions that are almost identical to the normal distribution curve, but a little bit shorter and broader, as shown in **Figure 29**.

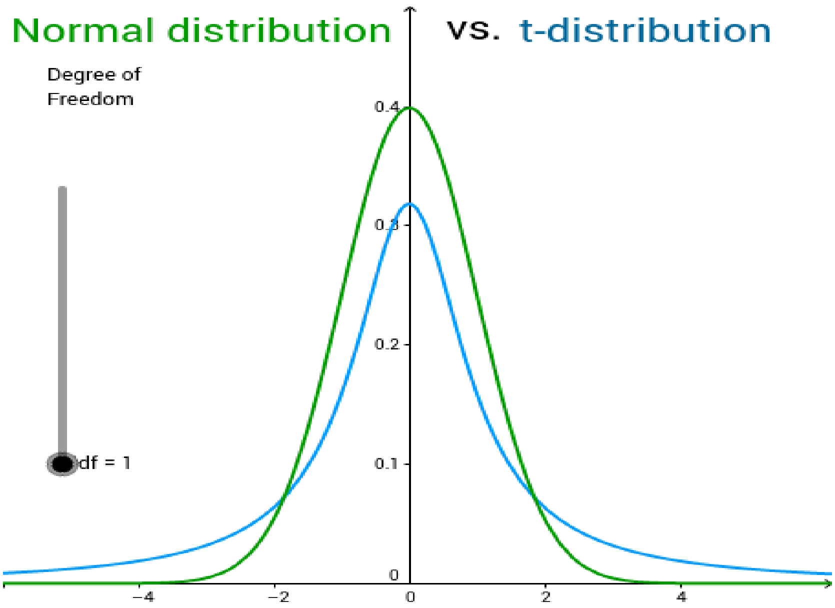


Figure 29. A comparison between the normal distribution and t-distribution

The first step in calculating the T- distribution, according to Senn and Richardson (1994), starts with knowing the degree of freedom. The degree of freedom is the sample size minus one. Then, the alpha level or the significance level, which is the probability of making a wrong decision when the null hypothesis is proven, could be either given directly, and the most common values are (0.5, 0.1), or calculated by subtracting the confidence interval from one. A null hypothesis is a hypothesis that says there is no statistical significance between the two variables. There is a standardized statistic test so-called the T-score represented as "t" and it could be used when the real value of standard deviation is unknown, and the size of the sample is under 30. The formula of T-score is given as follows:

$$t = \frac{\bar{x} - \mu_0}{\frac{s}{\sqrt{n}}}$$

Equation 8. T score formula

t: T-score, $\bar{x}$: sample mean, μ_0: the population mean, μ_0: sample standard deviation, n: sample size.

It is feasible to use Excel to compute the two-tailed inverse of the Student's T-distribution value by using the following function:

TINV (probability, deg_freedom)

Probability = The percentage value of observations to the right of the corresponding t value.

Deg_freedom = Number of degrees of freedom to use, and it equals the number of replications -1.

The T-distribution value in the student or T-test in this study is computed for one tail, or one side because the simulation model is designed for the future state to show that it is more effective than the current one. Thus, the future model will not be compared to the current one if it is less efficient, and this is due to the reason that it is not required. Besides, the one-tailed test provides more power to detect an effect in one direction. In the next section, the conception of the confidence interval is explained.

- **Confidence interval**

The confidence interval is a type of interval estimate, and it is used to appraise the accuracy of a sample that might contain the actual value of a population parameter (values of mean and standard deviation). It is associated with the confidence level that represents the frequency of the available confidence interval that contains the actual value of the population parameter. The confidence intervals are composed of a range of possible values of a population parameter; however, it is not necessarily for the taken sample to contain the real value because the confidence interval influences the size of the taken sample, the confidence level, and the variability in that sample. It is most common that a 95% confidence level is used (Kendall and Stuart, 1973). According to (Kendall and Stuart, 1973), the confidence interval could be calculated based on the T-distribution provided the actual standard deviation unknown, and the number of replications under 30 using the following formula:

$$\overline{\boldsymbol{x}}(\boldsymbol{n}) = \mp \boldsymbol{t}_{\boldsymbol{n}-1,1-\frac{\alpha}{2}} \sqrt{\frac{\boldsymbol{s}^2(\boldsymbol{n})}{\boldsymbol{n}}}$$

Equation 9. Confidence interval formula

$\bar{x}\,(n)$: the mean value, $1 - (\frac{\alpha}{2})$: One-sided confidence interval, t: t-distribution, s: standard deviation of the replications mean, n: number of replications.

After having a quick review of the T-distribution and the confidence interval concepts, it is possible now to start applying the steps of replications analysis. In this analysis, all equations of the relative connotations are introduced, such as the standard deviation and the standard error formulas. Besides, the two approaches used to calculate the number of required replications are introduced. The first approach is the relative precision approach, and the second one is the absolute precision approach, and all of that is explained in the next section.

4.4.7.1 Replication analysis

This study aims to indicate precisely the number of required replications to make sure that the obtained results are reliable and could be considered as a reference for further experiments. The inputs of simulation models are naturally probabilistic and variable. This variability causes some variation in the model outputs, and because of that, it is inappropriate to do a single simulation run or replication. For the sake of reducing the variability, which will result in making a wrong decision based on the outputs, a particular number of replications must be performed or run. The first typical number of replications is found to be ten, and this gives reasonable statistical confidence before adding the subsequent or additional replications which are required. The following are the subsequent steps of replication analysis (Chung, 2003):

1. Calculate the mean and standard deviation (STDEV) of the ten replications mean. This step is the commencement of the replication analysis process, and it requires the simulation model to be finished. Thus, the simulation model should be run for ten replications, and the summary statistics values to be written down. The designed simulation model, in this case, is done for vehicle scheduling in a manufacturing firm, and then it has been validated with the company's expert, so the results are reliable. The following tables, **Table 8** and **Table 9**, show the average mean value and the standard deviation of the throughput and WIP after running the simulation model with ten replications.

Rep.no	1	2	3	4	5	6	7	8	9	10
Throughput	33.940	33.937	33.944	33.94	33.931	33.938	33.946	33.95	33.936	33.944
Average mean	33.951									
STDEV	0.00833									

Table 8. The average mean value and standard deviation of throughput

Rep.no	1	2	3	4	5	6	7	8	9	10
WIP	1475.5	1475.5	1475.5	1475.5	1475.57	1475.56	1475.56	1475.56	1475.55	1475.5
Average mean	1475.5									
STDEV	0.0091									

Table 9. The average mean value and standard deviation of WIP

The standard deviation amounts are extracted from the simulation model after running some experiments using the simulation software tool that gives the average value of standard deviation. In Excel, it is possible to use the function **Sted ()** to calculate the standard deviation magnitude. Another way to do that is to calculate the standard deviation manually by using the upcoming equation:

$$\boldsymbol{S} = \sqrt{\frac{\sum_{1}^{n} \bar{x}_{\iota} - \bar{\bar{x}}}{n-1}}$$

Equation 10. Standard deviation formula

$\bar{x}_{\iota}$ = the replication averages, $\bar{\bar{x}}$ = the average of replication average, n = sample size.

2. Calculate the standard error of the data. The summary statistics of the previous step beside T-distribution and confidence interval values are used to calculate the standard error of data under study. The formula of the standard error is given as follows:

$$\boldsymbol{Standard\ Error} = (t_{1-\frac{\alpha}{2},n-1}) * s/\sqrt{n}$$

Equation 11. Standard error formula

s = standard deviation of the replication means, n = number of replications or sample size.

In this study, the initial number of replications is n = 10 and α = 0.05 since the selected confidence interval is 95%. From the T-distribution table and for one-sided T-test, the value of $(t_{1-\frac{\alpha}{2},n-1})$ = 1.833, and the values of standard deviation for throughput and WIP are 0.00833 and 0.0091, respectively. By compensating for all previous values in the equation (2), standard error magnitudes could be computed.

Throughput standard error = (1.833*0.00833) / √10 = 0.004828.

WIP standard error = (1.833*0.00911) / √10 = 0.005274.

In Excel, it is possible to calculate the standard error by using the following equation:

TINV (probability, Deg_freedom) *STDEV/(N)^0.5

3. Select the level of precision. After calculating the standard error, it is time to determine how many replications are needed. However, in order to do that, it is required to select a level of error that is suitable for this kind of study. There are two approaches to indicate the acceptable level of precision objectively. The first approach is grounded on an absolute comparison of the standards error to a particular tolerance level. The second approach is based on a relative value of the standard error in comparison to the sample mean. In this study, both approaches would be discussed in the subsequent sections.

- **Absolute precision approach**

In this approach, a level of tolerance for precision is indicated based on the resulted number of standard errors. In other words, an additional number of replications needs to be run to reduce the standard error to the chosen number of precisions. The standard error of throughput is 0.004828 and 0.005274 for WIP, those numbers are small, and they give a good indicator that the model is reliable due to the finite level of variability. However, it is still possible to reduce them a little bit, and the exact number will be chosen depending on the nature of the project and previous experiences. The value of absolute precision of the throughput can be selected at 0.004, and WIP can be 0.005. Since the resulted standard error should be reduced to the desired absolute precision, the formula of standard error can be used as follows:

$$\boldsymbol{Absolute\ Precision} = (\boldsymbol{t}_{\boldsymbol{1-\frac{\alpha}{2},n-1}}) * \boldsymbol{s}/\sqrt{\boldsymbol{n}}$$

Equation 12. Absolute precision formula

The previous equation could be rearranged and solved for the new number of replications which match the desired level of absolute precision:

$$i = \left(\frac{t_{1-\frac{\alpha}{2},n-1} * s}{\text{Absolute Precision}} \right)^2$$

Equation 13. Number of replications based on the absolute precision approach

In Excel, it is possible to calculate the number of replications needed to achieve absolute precision by using the following formula:

((TINV (Probability, Deg_freedom) *STEDV) / Absolute precision)) ^2

The next step is to verify that the previous number of required replications is sufficient. The number of simulations needed is calculated, and it equals 14.57298 for throughput and 16.95 for WIP. These numbers need to round up, so they will be 15 and 17, respectively. Therefore, the simulation model will be run for 17 replications since the biggest number is 17, and the simulation model is the same for the throughput and the WIP. After running the simulation model, it is possible to observe that summary statistics are different from the first ones because the number of replications is not the same. The new statistics would be used to calculate the new standard error and compare it to the selected level of absolute precision. The standard errors of throughput and WIP are 0.003167 and 0.003345, respectively. Since both numbers are smaller than the selected absolute precisions, so the 17 replications are sufficient for this study. The last thing about this method; depends on the experience of practitioners; also, the opting of the desired level of precision is done arbitrarily.

- **Relative precision approach**

This method is more preferred to the first one because it is not necessary to select an arbitrary absolute precision level. This method can overcome the arbitrary selection of precision level by dividing the value of standard error by the sample mean value. The standard error should be small in comparison to the sample mean value for a powerful and robust statistical analysis. A typical value for the desired level of relative precision is 0.09, and the resulted relative precision would be compared to it. The equation of relative precision is given as follows:

$$\text{Relative precision} = \frac{t_{1-\frac{\alpha}{2},n-1} * s / \sqrt{n}}{\bar{\bar{x}}}$$

Equation 14. Relative precision formula

n = number of replications, $\bar{\bar{x}}$ = mean of the replication means.

Since the resulted relative precision values are less than 0.009, so ten replications are sufficient to run the simulation model at that number of replications and proceed with the optimization process. A further step to confirm that the selected number of replications is adequate to run the simulation model for that number is to use the equation of relative precision after rearranging it in a way that isolates the number of replications in one side of the equation and other parameters in the other side:

$$\mathbf{i} = \frac{\mathbf{t}_{\mathbf{1}-\frac{\alpha}{2},\mathbf{n}-\mathbf{1}} * \mathbf{s}}{\textbf{Relative precision} * \bar{\bar{\mathbf{x}}}}$$

Equation 15. The number of replications based on the relative precision approach

i = number of replications needed to achieve the relative precision.

In Excel, the implementation of the previous equation is as follows:

((TINV (Probability, Deg_freedom) *STDEV) / (Relative precision*Average mean)) ^2

After applying the two methods, it is evident that they give different results. However, the first one, which is the absolute precision, depends on the arbitrary selection of precision level, and it is not entirely accurate. On the other hand, the second method, which is relative precision is more reliable because it gives the level of precision as a percentage between the standard error and the average mean of data under study. Therefore, the final chosen number of replications would be 10. After conducting the replication analysis, it is possible to proceed with the steady-state analysis explained in the following section.

4.4.7.2 Steady-state analysis

The study state analysis is the process of getting general information about the necessary period to run the model before reaching a steady state. In other words, at the beginning of the simulation, the production lines are empty, and some time is needed to load them with the corresponded material until the regular operation is reached; that time is known as the warm-up time, and in this case, it is measured in days. In reality, the lines are full of material, and they are never empty, and the work is continued from the same point in which it stopped the previous day. In the Facts Analyzer program, there is a Tab enables the designer to put the different settings of steady analysis. Figure 30, shows the settings that were chosen to get the necessary period before getting the model in the steady-state.

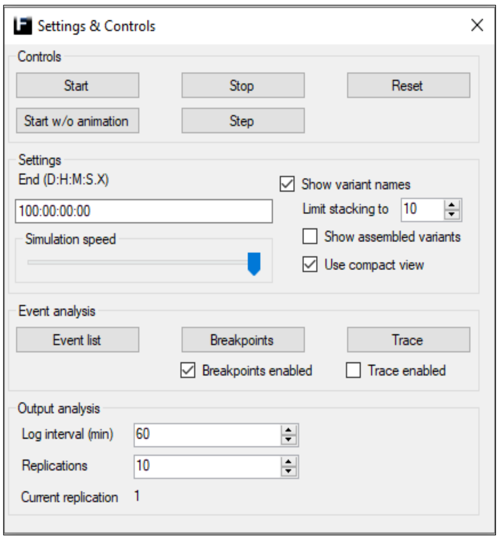


Figure 30. Settings of steady-state analysis

It shows that the simulation horizon was set to 100 days to give an extra safety period and make sure the model has been run enough so the result would be reliable. The log interval was set to 60 minutes to be able to analyze the data in the obtained charts, and the number of replications was selected to be equal to 10, as explained before.The model was run under this condition, and the outcomes were obtained, the two most common parameters in this kind of study are the hourly throughput and WIP, so they have been chosen to represent the results. The following figure, Figure 31, represents the behavior of the simulation model in terms of throughput.

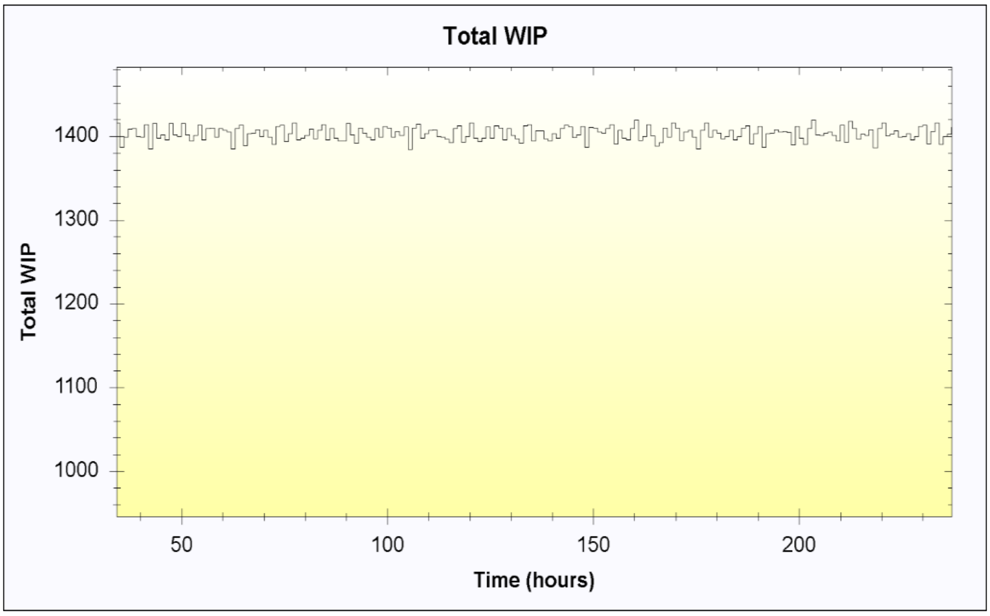


Figure 31. Graphical output of throughput after running the steady-state analysis

The simulation model's behavior concerning WIP is also shown in the following figure, Figure 32.

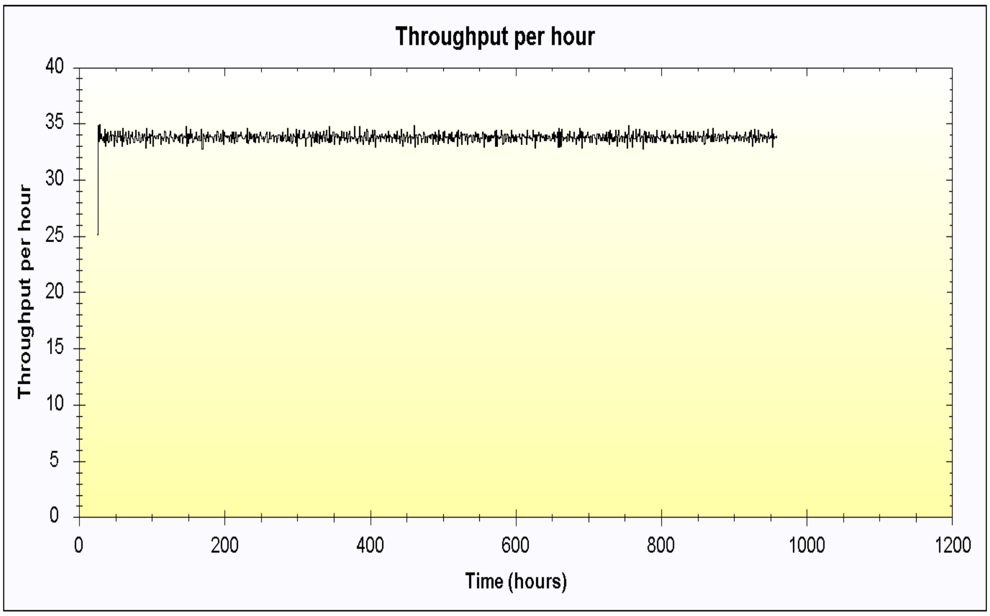


Figure 32. Graphical output of WIP after running the steady-state analysis

By analyzing the previous figures, it is easy to notice that the model emerges the steady-state approximately 33 hours after running the analysis. Therefore, it could be said that the necessary warm-up time is 33 hours, and that means that two days have to be selected as a warm-up time before running different experiments. As the process of model verification and validation done and the variability study is completed, it is possible to proceed with the next step, which is the design of the "What-if" scenario.

4.4.8 Design of "what-if" scenario

Once the simulation models were verified and validated, it was possible to start with designing different scenarios that have some changes from the basic one. Three alternatives were introduced, and each one deals with a different aspect of the design, then the results were compared with each other to check the advantages and disadvantages of them. The three main scenarios are:

- To increase the demand by 100%.
- To change the location of the material preparation area.
- To change the way by which AGVs deliver material to assembly lines.

4.4.8.1 The first improved scenario

The first scenario, to increase the throughput by 100%, was implemented on the model and was done by decreasing the process times of assembly lines by 50%. After implementing this scenario, it is evident that the lead time was decreased to half. The following table, Table 10, shows the new process Table 10 times of production lines. All process times are measured in minutes.

Variant name	Kit-A-1	Kit-B-1-1	Kit-B-2-1	Kit-B-3-1	Kit-C-1-1	Kit-C-2-1	Kit-D-1-1	Kit-D-2-1
Process time	2.20	4.13	7.05	6.51	10.25	32.15	34.05	107.08

Table 10. The different process times of each variant of the first scenario

4.4.8.2 The second improved scenario

The second scenario, to change the location of the material preparation area, was implemented by shifting the place of the supermarket. The new place is shifted to be in the center of the opposite area located in the front of assembly lines, as shown in Figure 33.

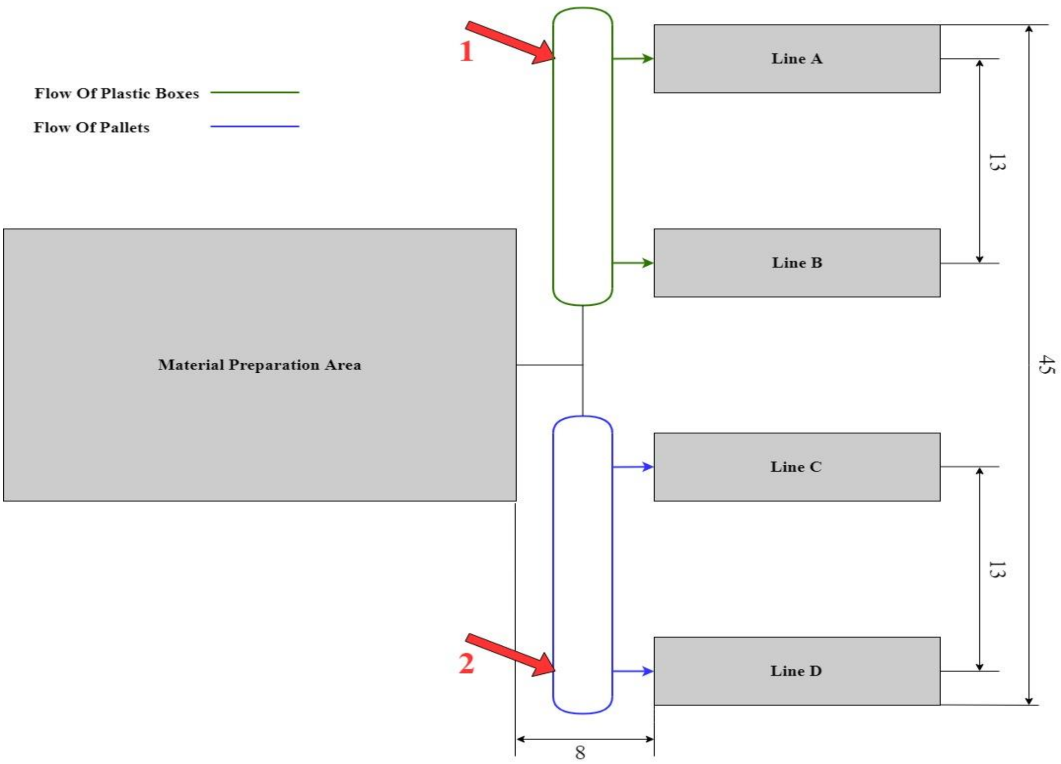


Figure 33. The new layout of the second scenario

As shown in the previous figure, the distance between the material preparation area and assembly lines are changed. The path that the first type of AGVs follows to deliver parts of small product sizes was named 1. The path 2 is the path that the second type of AGVs follows to deliver parts of mid-range products. Going through the results shows that the lead time is decreased slightly.

4.4.8.3 The third improved scenario

The third scenario, to change the way by which AGVs deliver material to assembly lines, was implemented on the model and done by modifying the material handling area in the basic model. The new delivering method decreased the lead time significantly because the AGVs are serving the assembly lines under the traveling kits process that explained before. In this scenario, each type of AGVs serves the two lines that produce the same size of products during the same cycle before going back to the starting point to load kits and starting a new cycle. This scenario is designed to improve the basic model, and it proved its effectiveness on the one hand. On the other hand, it was decided to use this model to compare it to a mathematical model for a validation purpose. However, it was found that results were hard to be compared since some data cannot be modeled in the simulation model. Therefore, it would proceed with this model as one of several scenarios designed to improve the basic model. The differences between this scenario and the basic model are presented in the next paragraph:

- The capacity of the first type of AGVs varies from 1 to 6 instead of waiting to be fully loaded.
- Lines of the same product size served during the same cycle.
- Empty boxes do not go back to MPA, and instead, they go outside the simulation model.

The next figure, **Figure 34**, shows the simulation model of this scenario, it is shown on the next page.

The next chapter is Results and Analysis. In this chapter, different results of the basic model and the improved scenarios are presented and analyzed. Besides, the obtained results from running the optimization process for the basic model and the third improved scenario are introduced.

Moreover, all input and output variables of the optimization engine are given.

Furthermore, the different inserted formulas in the optimization process are shown. Finally, the acquired charts for different parameters are presented at the end of this chapter. In the next chapter, Chapter 6, a brief discussion of these results is presented. Then, some conclusions and future works are presented in Chapter 7.

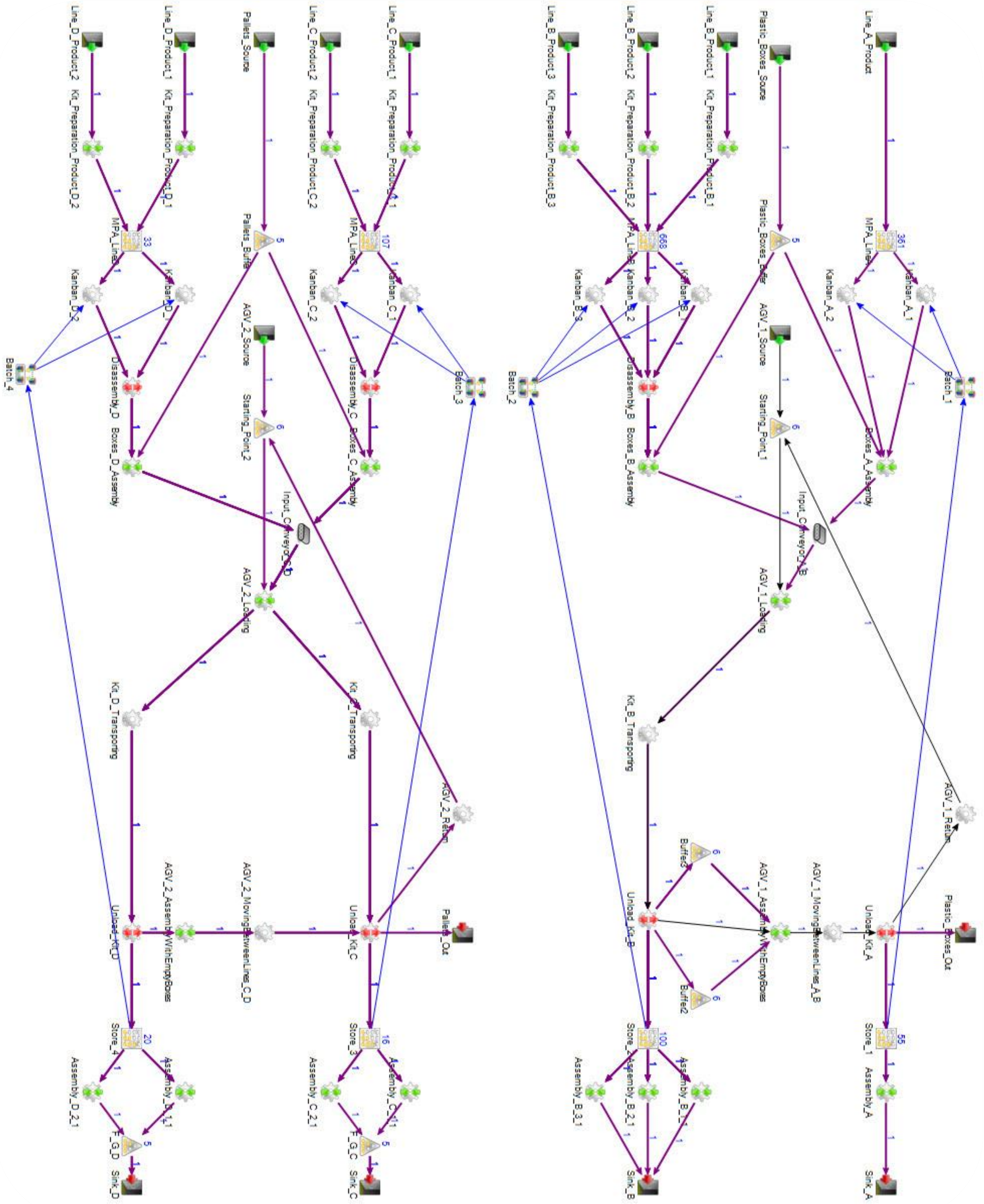


Figure 34. The simulation model of the third scenario

5 Results and Analysis

In this chapter, the results of the basic model and the results of improved scenarios are presented and discussed. The results of improved scenarios are compared with the basic simulation model. The results were analyzed comparing different parameters, and those parameters are measured to evaluate the system performance; then, they are presented in the following tables:

5.1 Results of the basic model (BM)

This simulation model is the basic one that all improved scenarios are compared to it. The next table, **Table 11**, shows the obtained results after running the simulation model.

	Throughput (product/h)	Lead time (sec)	WIP (kits)	Produced parts (parts)
Plant	33.82	111706.8	1400.4	22727
Kit-A-1	12.9	55238.97	197.98	8671
Kit-B-1-1	7.114	156606.86	309.5	4781
Kit-B-2-1	4.23	156158.27	183.5	2843
Kit-B-3-1	4.6	157572.75	201.5	3093
Kit-C-1-1	2.88	107500	86	1935
Kit-C-2-1	0.93	116130	30	625
Kit-D-1-1	0.88	122730	30	591
Kit-D-2-1	0.28	141427	11	188

Table 11. Results of the basic model

The table shows that the values of lead time, WIP, and throughput of kits that compose different products. It shows obviously that the throughput increases when the WIP raises as well. In addition, it shows that the lead time value of line B is the largest, and this regular since three kits are needed at this line to form one product. The focus is on the values of the plant because it is used for a comparison purpose with other improved scenarios.

5.2 Results of scenario 1 (Sce-1)

This scenario is about to increase demand by 100%. The next table, Table 12, shows the obtained results of this scenario.

	Throughput (product /h)		Lead time (sec)		WIP (kits)		Produced parts (parts)	
	Sce-1	BM	Sce-1	BM	Sce-1	BM	Sce-1	BM
Plant	67.64	33.82	68287	111707	1345	1400.4	45454	22727
Kit-A-1	25.8	12.9	30664	55239	207	197.98	16339	8671
Kit-B-1-1	14.228	7.114	114541	156607	303	309.5	9562	4781
Kit-B-2-1	8.46	4.23	92157	156158	180	183.5	5686	2843
Kit-B-3-1	9.2	4.6	101187	157573	198	201.5	6186	3093
Kit-C-1-1	5.76	2.88	55616	107500	89	86	3871	1935
Kit-C-2-1	1.86	0.93	59769	116130	31	30	1255	625
Kit-D-1-1	1.76	0.88	63369	122730	31	30	1183	591
Kit-D-2-1	0.56	0.28	70768	141427	11	11	376	188

Table 12. Results of the first scenario

The table demonstrates the results of the first scenario compared to the basic model. It shows that the throughput and the produced parts values have been doubled since the assembly times of production lines were reduced to half to achieve this purpose. Besides, the values of the lead time of lines C and D that produce products of mid-range size have been decreased by 50% and by 37% for lines A and B that produce products of small sizes. The mean value of the new lead time is 68287 (sec), and it represents 39% less than the previous value, and this is a significant reduction compared to the basic model.

5.3 Results of scenario 2 (Sce-2)

In this scenario, the location of the supermarket or MPA is changed. As a result, the distances between MPA and different assembly lines are changed. The next table, Table 13, contains the acquired results. of the second scenario.

	Throughput (product/h)		Lead time (sec)		WIP (kits)		Produced parts (parts)	
	Sce-2	BM	Sce-2	BM	Sce-2	BM	Sce-2	BM
Plant	33.82	33.82	109814	111707	1401	1400.4	22727	22727
Kit-A-1	12.9	12.9	55239	55239	197.98	197.98	8671	8671
Kit-B-1-1	7.114	7.114	156607	156607	309.5	309.5	4781	4781
Kit-B-2-1	4.23	4.23	156158	156158	183.5	183.5	2843	2843
Kit-B-3-1	4.6	4.6	157573	157573	201.5	201.5	3093	3093
Kit-C-1-1	2.88	2.88	107500	107500	86	86	1935	1935
Kit-C-2-1	0.93	0.93	116130	116130	30	30	625	625
Kit-D-1-1	0.88	0.88	122730	122730	30	30	591	591
Kit-D-2-1	0.28	0.28	141427	141427	11	11	188	188

Table 13. Results of the second scenario

The table illustrates the results of the second scenario compared to the basic model. The plant's lead time is decreased by roughly 2%, and the other values of different products are the same as the basic model. The reason behinds this is that changing the location of the supermarket affects the transportation time only, which constitutes a small proportion of the whole lead time, and consequently, the plant's lead time stays almost the same.

5.4 Results of scenario 3 (Sce-3)

In this scenario, the way of material delivery that followed in the basic model is changed. Here, the traveling kits process explained earlier in this report will be adapted. Then, the two types of kitting can be compared to each other to identify the one that fits best for this study. The next table, Table 14, illustrates the obtained results of this scenario and compare them to ones of the basic model.

	Throughput (product/h)		Lead time (sec)		WIP (kits)		Produced parts (parts)	
	Sce-3	BM	Sce-3	BM	Sce-3	BM	Sce-3	BM
Plant	33.82	33.82	32675	111707	1324	1400.4	22727	22727
Kit-A-1	12.9	12.9	55241	55239	197.98	197.98	8670	8671
Kit-B-1-1	7.114	7.114	156354	156607	309	309.5	4781	4781
Kit-B-2-1	4.23	4.23	155733	156158	183	183.5	2843	2843
Kit-B-3-1	4.6	4.6	157182	157573	201	201.5	3094	3093
Kit-C-1-1	2.88	2.88	107500	107500	86	86	1935	1935
Kit-C-2-1	0.93	0.93	116130	116130	30	30	625	625
Kit-D-1-1	0.88	0.88	122730	122730	30	30	591	591
Kit-D-2-1	0.28	0.28	141427	141427	11	11	188	188

Table 14. Results of the third scenario

The table shows the results of the last scenario that focuses on how AGVs deliver the material into assembly lines. It decreased the plant's lead time by more than 70%, and this gives a strong signal of how much the material handling system influences the whole industrial system and lead time in particular, which affects the total productivity. Moreover, the applied material handling system plays a significant role in reducing wastes that come from unwanted movements and extra cycles that do not add value to the whole production process. Thus, the traveling kits process is more suitable than the stationary kits process since it gives better results than the stationary kitting. The final decision is up to the company staff to choose which material delivery method they want to have. The next part of the project was to run the optimization process to improve the obtained results related to these project objectives. The next sections illustrate the outcomes of running the optimization process.

5.5 Results of optimization

After running two optimizations with 5000 iterations each, the first one was carried out for the basic model and the second one for the third scenario. As mentioned previously, NSGA-III was selected as the algorithm which would be used as the optimization method since it is built in the simulation software tool, and it suits cases where multi objectives need to be fulfilled. The main objectives of the optimization are to reduce both the number of used vehicles and capacities of line-side buffers besides some other objectives mentioned in the section of thesis objectives; hence, the focus will be on them. The input and output variables are represented in the following figure, **Figure 35**.

Input Variables:

<table>
<tr><th>Name</th><th>Data Type</th><th>Set</th></tr>
<tr><td>AGV_1_Source_CreationN...</td><td>INTEGER</td><td>{1;5|1}</td></tr>
<tr><td>AGV_2_Source_CreationN...</td><td>INTEGER</td><td>{1;5|1}</td></tr>
<tr><td>Store_2_Capacity</td><td>INTEGER</td><td>{48;96|1}</td></tr>
<tr><td>Store_1_Capacity</td><td>INTEGER</td><td>{26;52|1}</td></tr>
<tr><td>Store_3_Capacity</td><td>INTEGER</td><td>{8;16|1}</td></tr>
<tr><td>Store_4_Capacity</td><td>INTEGER</td><td>{3;6|1}</td></tr>
<tr><td>Store_A_Capacity</td><td>INTEGER</td><td>{52;361|1}</td></tr>
<tr><td>Store_B_Capacity</td><td>INTEGER</td><td>{96;668|1}</td></tr>
<tr><td>Store_C_Capacity</td><td>INTEGER</td><td>{16;107|1}</td></tr>
<tr><td>Store_D_Capacity</td><td>INTEGER</td><td>{6;33|1}</td></tr>
<tr><td>Conveyor_D_Length</td><td>REAL</td><td>{2;10|1}</td></tr>
<tr><td>Conveyor_A_Length</td><td>REAL</td><td>{2;10|1}</td></tr>
<tr><td>Pallets_Input_Length</td><td>REAL</td><td>{2;10|1}</td></tr>
<tr><td>Plastic_Boxes_Input_Length</td><td>REAL</td><td>{2;10|1}</td></tr>
<tr><td>Conveyor_C_Length</td><td>REAL</td><td>{2;10|1}</td></tr>
<tr><td>Conveyor_B_Length</td><td>REAL</td><td>{2;10|1}</td></tr>
</table>

Output Variables:

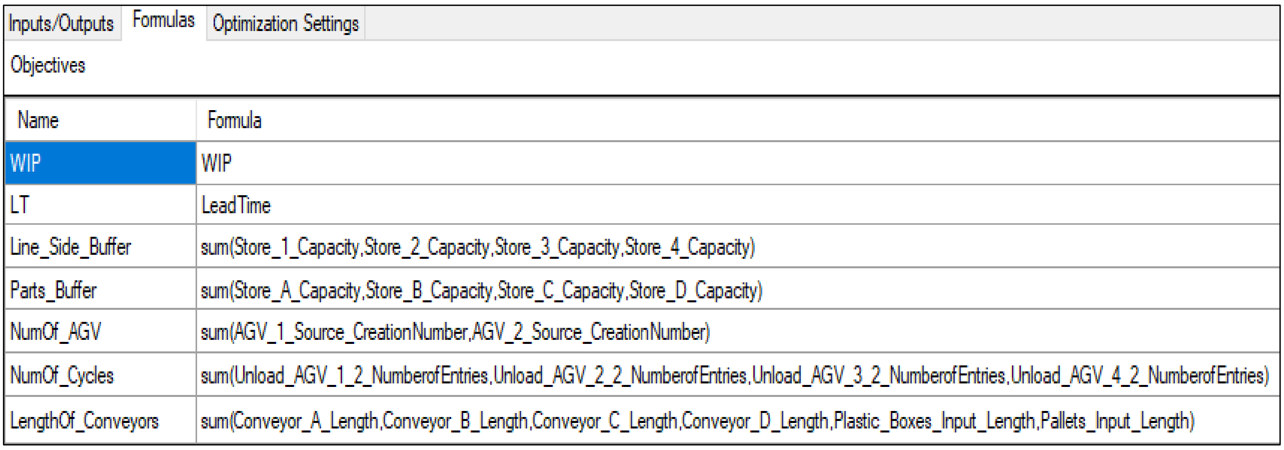
Name
Unload_AGV_1_2_NumberofEntries
Unload_AGV_2_2_NumberofEntries
Unload_AGV_3_2_NumberofEntries
Unload_AGV_4_2_NumberofEntries
LeadTime
WIP

Figure 35. Input and output variables of the optimization process

As shown in the above figure, different input and output variables of the optimization engine are inserted. The first two decision variables represent the upper and lower bounds of the number of used AGVs, where they were selected to be between (1 and 5). The next four variables represent the capacities of line- side buffers and the lower bounds set to values that equal one-hour production, and the upper bounds are equal to values of two-hours production. The bounds of capacities of parts' buffers located at MPA were decided to be between two-hours production for the lower bound and one-day demand for the upper bound. The last six variables are the bounds for different conveyors located at production lines and MPA; they were chosen to be between 2 and 10 meters and following the dimensions of pallets and plastic boxes that were selected according to European standard sizes.

The selected software tool for this study does not give the possibility to assign the number of cycles in a straightway, and this puts a necessity to find an alternative way. That way is to assign the number of entries that each AGV makes when it unloads empty boxes before starting a new cycle. Thus, the number of cycles represents the first four outputs, one for each production line, and then WIP and lead time to represent the rest. Under the "set" column in Figure 35 and for every input, the base values that equal to one represent the step between every two sequential values of the lower and the upper bounds. This step acts for an integer value, for example, the lower and upper limits of the number of AGVs moves one integer value from 1,2,3,3….,10. This means that it is not possible to have a fractional value to represent the number of AGVs.

The next figure, **Figure 36**, shows the formulas used in the optimization, and in here, different objectives of the studied project are consigned.



Inputs/Outputs | Formulas | Optimization Settings

Objectives

Name	Formula
WIP	WIP
LT	LeadTime
Line_Side_Buffer	sum(Store_1_Capacity,Store_2_Capacity,Store_3_Capacity,Store_4_Capacity)
Parts_Buffer	sum(Store_A_Capacity,Store_B_Capacity,Store_C_Capacity,Store_D_Capacity)
NumOf_AGV	sum(AGV_1_Source_CreationNumber,AGV_2_Source_CreationNumber)
NumOf_Cycles	sum(Unload_AGV_1_2_NumberofEntries,Unload_AGV_2_2_NumberofEntries,Unload_AGV_3_2_NumberofEntries,Unload_AGV_4_2_NumberofEntries)
LengthOf_Conveyors	sum(Conveyor_A_Length,Conveyor_B_Length,Conveyor_C_Length,Conveyor_D_Length,Plastic_Boxes_Input_Length,Pallets_Input_Length)

Figure 36. The different objectives of this project

As mentioned before, the main objectives were to minimize the number of vehicles and line-side buffers. Besides, some additional objectives were assigned, such as minimizing the capacities of part buffers, lengths of conveyors, WIP, and lead time. The optimization algorithm to be followed is NSGA-III, and it is run with 5000 iterations, and the results were obtained and discussed further in this section.

5.5.1 The optimization results of the basic model

The next figure, **Figure 37**, shows the plot of lead time on the Y-axis and the total number of AGVs on the X-axis. It shows the result of running the 5000 iterations of the optimization process, where each point represents a feasible solution.

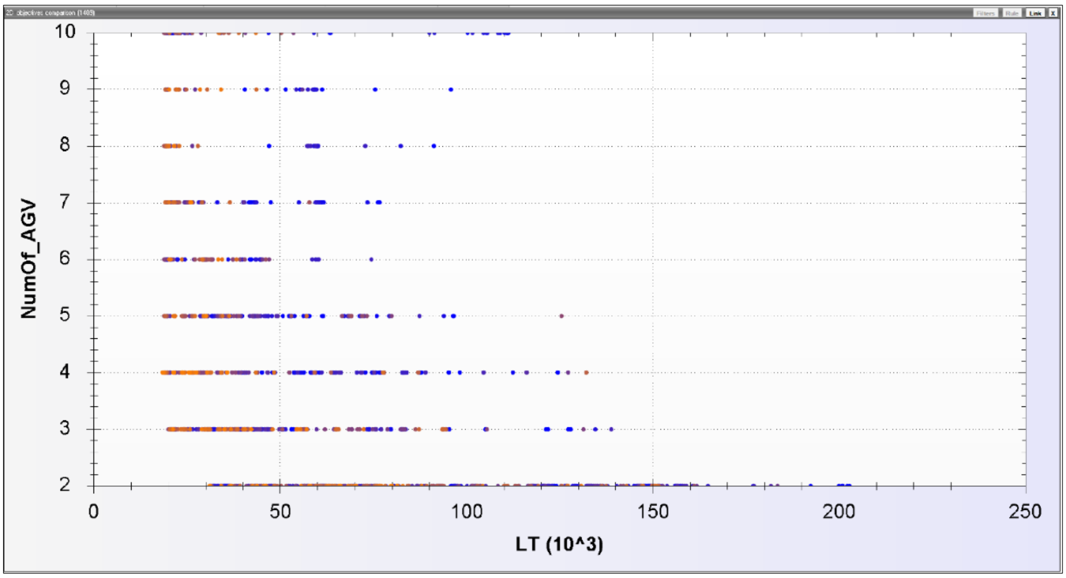


Figure 37. 2D-plot of LT and Numof_ AGV for the basic model

As shown in Figure 37, the lead time (LT) is compared to the number of AGVs (Numof_AGV). Pareto optimal front could be drawn, and it shows that the minimum number of AGVs which is required to perform the material handling process is 2 (1 AGV for pallets and another 1 for plastic boxes). The corresponded value of lead time that AGVs need to handle the required amount of kits is 30966 seconds, which is 516 minutes or 8.6 hours. The graph shows that going up one step on the Y-axis decrease the lead time significantly, where the new value is 20124 seconds and this a decrease of 35%.

The following figure, Figure 38, shows the number of vehicles of the first type AGV_1.

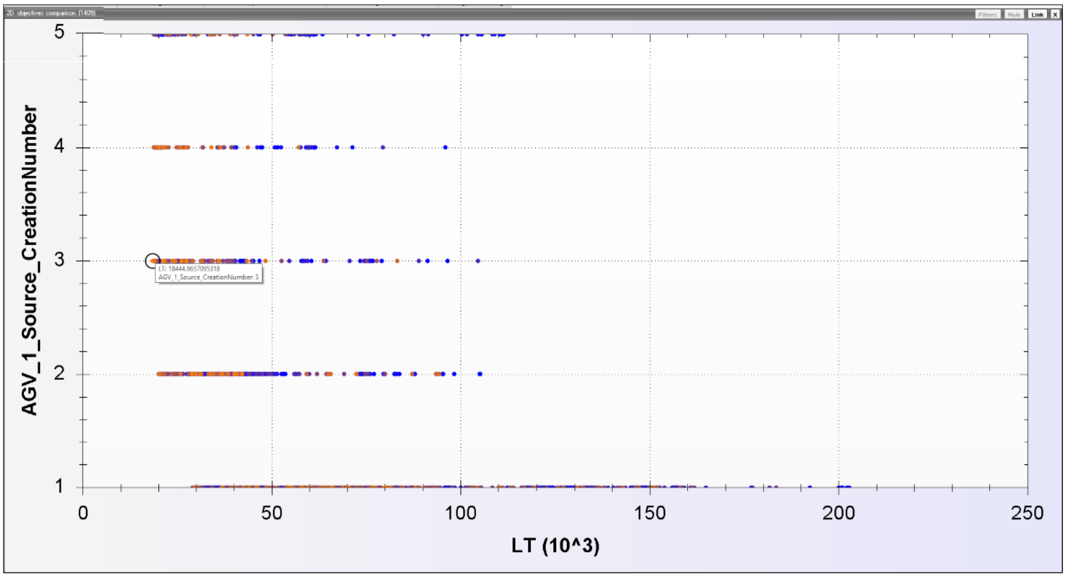


Figure 38. 2D-plot of LT and AGV_1_Source_CreationNumber

As Figure 38 shows, 3 AGVs of the first type is the best selection regarding the value of lead time and the total number of AGVs. However, the LT is not so different from choosing 2 AGVs, that is something to prioritize by the managers.

For the second type of vehicle AGV_2, it is shown in Figure 39 that one vehicle is required to deliver material to the assembly lines.

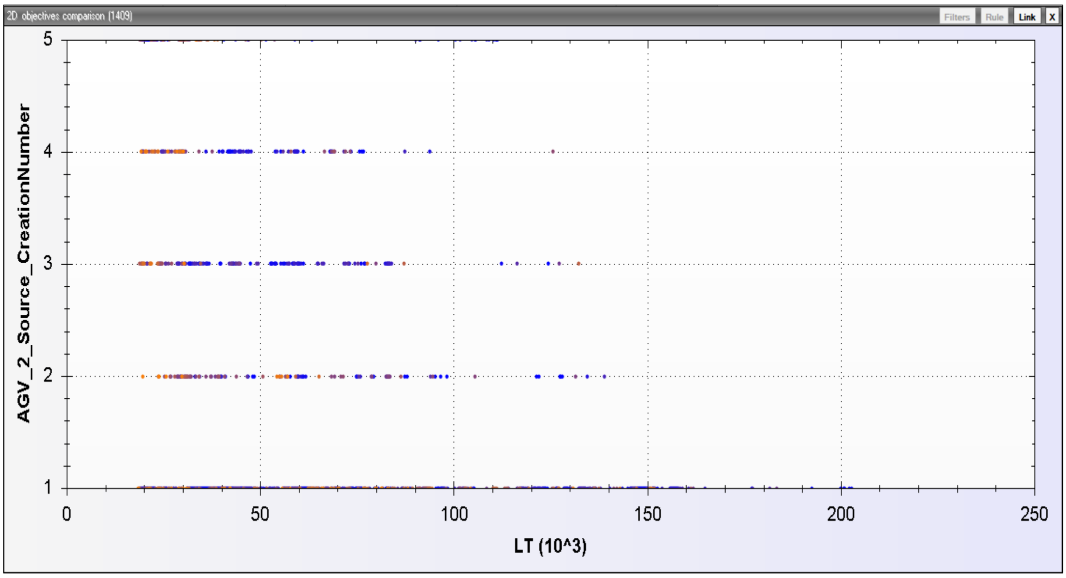


Figure 39. 2D-plot of LT and AGV_2_Source_CreationNumber

Therefore, two vehicles of the first type and one vehicle of the second type are required to perform the material handling process in this study, and it could be considered as the first alternative in terms of prioritization in the concerned company.

Moreover, the minimal value of lead time equals to 18445 seconds, as shown in Figure 37, and it could be achieved by assigning 4 AGVs. This selection represents the second alternative. It is noticed that the value of lead time stays constant after the previous magnitude, and this means that there is no benefit from assigning more AGVs to be put in service in order to deliver the material into assembly lines. The former selection gives the minimal lead time, and if it is going to be chosen, the number of necessary vehicles of each type would be 3 and 1, respectively, as shown in the previous chart.

The final decision about what alternative would be followed is totally up to the decision-makers in the company because it represents a trade-off between the two parameters. In other words, if the company concerns the number of AGVs more than the lead time, then the first alternative fits better. On the other hand, if the company gives priority to the lead time, then the second alternative is better than the first one.

The two following tables, Table 15 and Table 16, contain a comparison between the two former alternatives for the other objectives.

Evaluation list (1409)

Iteration	WIP	LT	Line_Side_Buffer	Parts_Buffer	NumOf_AGV	NumOf_Cycles	LengthOf_Conveyors	AGV_1_Source_CreationNumber	AGV_2_Source_CreationNumber
2650	296.6441310780...	20124.49993890...	110	170	3	7079.4	22	2	1

Table 15. The first alternative of the basic model

Evaluation list (1409)

Iteration	WIP	LT	Line_Side_Buffer	Parts_Buffer	NumOf_AGV	NumOf_Cycles	LengthOf_Conveyors	AGV_1_Source_CreationNumber	AGV_2_Source_CreationNumber
4902	322.1595696999...	18444.96570953...	97	170	4	8226.5	12	3	1

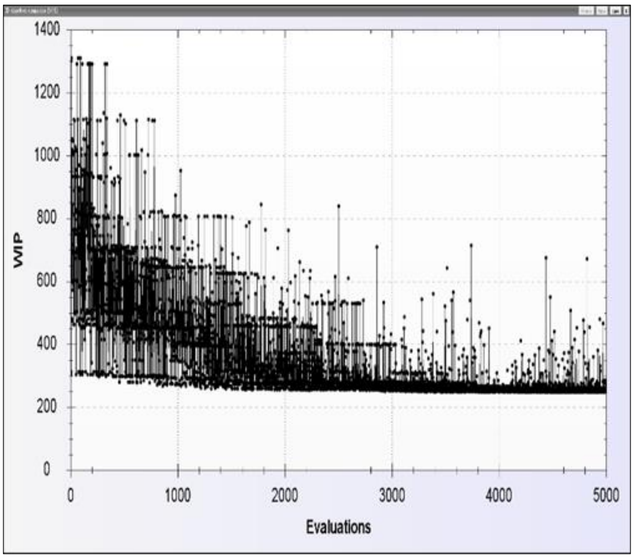
Table 16. The second alternative of the basic model

By having a close look into them, it could be said that the first scenario has some advantages in terms of WIP, the number of AGVs, and the number of cycles; whereas, the second scenario is better for lead time, line-side buffers and length of conveyors.

To verify the effectiveness of running the optimization process, the initial inputs of the basic model would be compared against the magnitudes, which are extracted after running the optimization process. The maximum initial number of AGVs, line-side buffers, length of conveyors were 12 AGVs, 170 store places, and 60 meters of conveyors, respectively. After the optimization process, the previous values for both alternatives became 3 or 4 AGVs, 110 or 97 store places, and 22 or 12 meters of conveyors. The capacities of line-side buffers have been reduced to the minimum possible amounts while maintaining the condition of one-hour production on the one hand. On the other hand, the number of AGVs has been reduced dramatically with keeping the condition, which says that shortage is not allowed according to the feeding policy of material.

5.5.2 The optimization results of the third improved scenario

In this scenario, the material is handled into assembly lines under the stationary kitting process, and the obtained results show significant improvements in different parameters. The value of lead time has been steadily decreased where the maximum magnitude was 32493 seconds at the beginning of the optimization process, the fifth iteration in particular, and it went down to the minimal value 5790 seconds (Figure 40). The same is true when it comes to Figure 41 that shows the dramatic decrease in WIP, where the value of WIP has been declined from 1310 to 212.



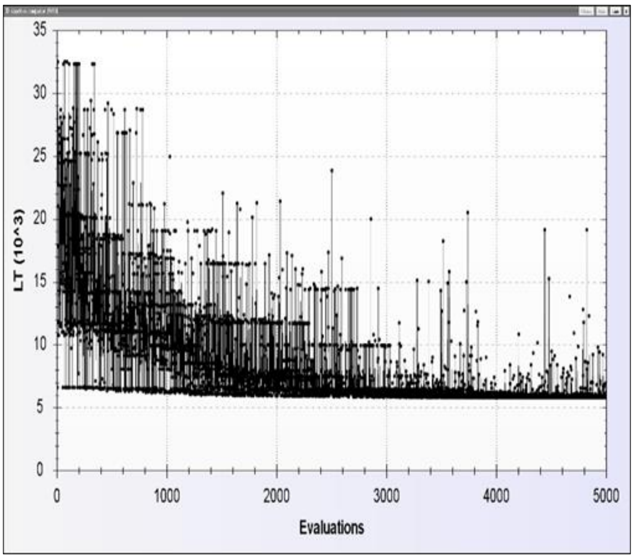
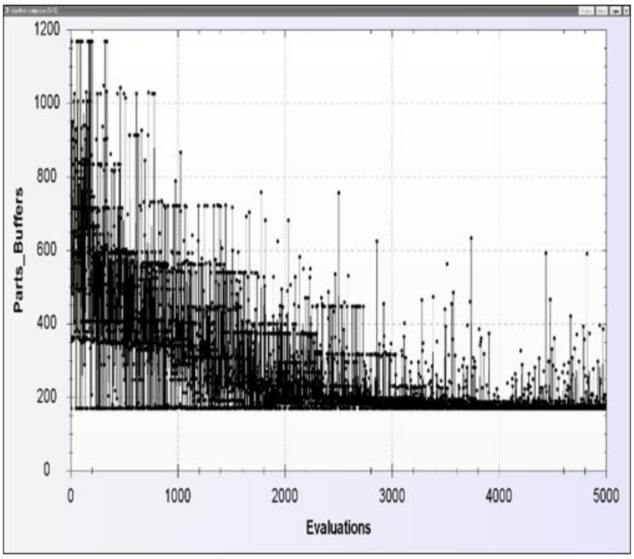


Figure 40. The evaluation of WIP

Figure 41. The evaluation of LT

The following figures, **Figure 42** and **Figure 43**, show the happened decrease in values of part buffers and line-side buffers, and it is easy to observe the significant improvements that come of this scenario, for example, the line-side buffers can be reduced till 89 with maintaining the condition that says the shortage is forbidden.



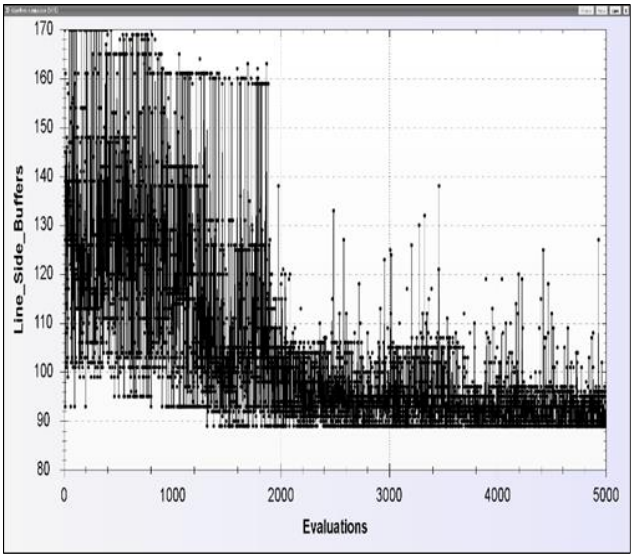


Figure 42. The evaluations of Part's buffers

Figure 43. The evaluations of Line-side' buffers

In the below figure, **Figure 44**, it can be appreciated that the Pareto-optimal front is located at the left bottom side of the graph, and it illustrates that the minimum necessary number of AGVs is two and the corresponded value of lead time is 11437 seconds.

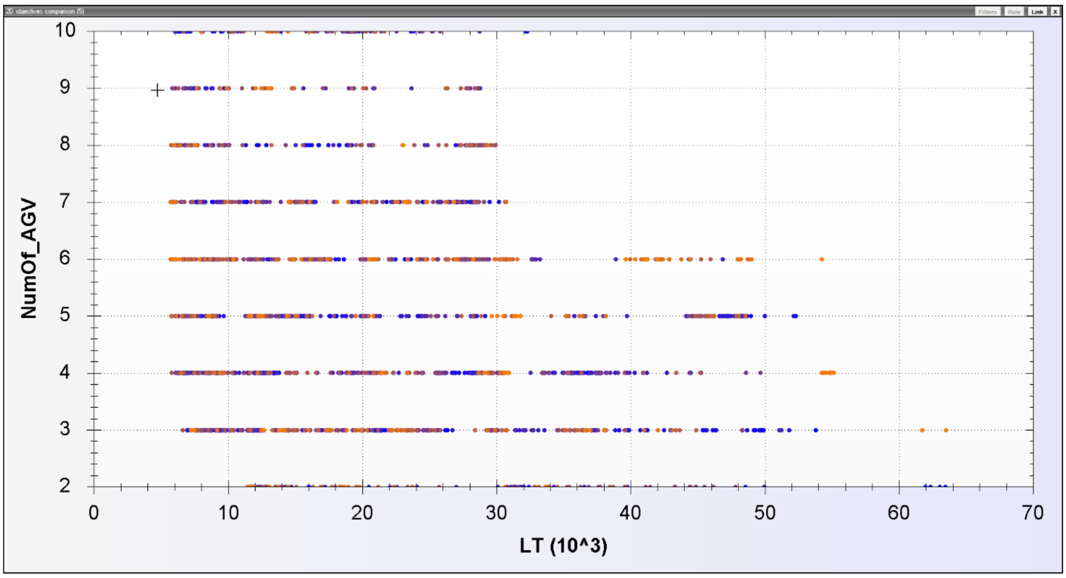


Figure 44. 2D-plot of LT and Numof_AGV for the third improved scenario

The previous figure shows that assigning 3 AGVs would decrease the value of lead time by 42%, where the new number becomes 6601 seconds. Thus, using three vehicles has a remarkable impact on the entire simulation model, and this was discussed in the previous chapter. In more detail, the number of AGVs of the first type is 2, and the second type is 1. Besides, the minimum lead time is obtained by consigning 4 AGVs, where it equals to 5790 seconds. However, the ultimate decision is up to the company.

The two following tables, **Table 17** and **Table 18**, show a comparison between the two previous alternatives concerning the other objectives.

Evaluation list (5)

Iteration	WIP	LT	Line_Side_Buffers	Parts_Buffers	NumOf_AGV	NumOf_Cycles	LengthOf_Conveyors	AGV_1_Source_CreationNumber	AGV_2_Source_CreationNumber
3316	219.0107174974...	6601.624587336...	127	170	3	46123	12	2	1

Table 17. The first alternative of the third scenario

Evaluation list (5)

Iteration	WIP	LT	Line_Side_Buffers	Parts_Buffers	NumOf_AGV	NumOf_Cycles	LengthOf_Conveyors	AGV_1_Source_CreationNumber	AGV_2_Source_CreationNumber
3275	247.2420013042...	5789.956263571...	87	170	4	52127.2	4	3	1

Table 18. The second alternative of the third scenario

The first resolution is better in terms of WIP, the number of AGVs, and the number of cycles. Nevertheless, the other resolution outnumbered the first one in three aspects, which are the lead time, the line-side buffers, and the length of conveyors.

6 Discussion

By analyzing the obtained results of the different designed scenarios, it is possible to notice the level of potential improvements that occurred. The results of the basic model show the values of principal parameters for each product's types and the plant as a whole. This model was designed as a future state consigning the data that is being used by the company in the current state, such as the daily demand of each variant, line storage for two hours of production. However, the focus was on modeling a future layout configuration of the main shop floor.

The purpose of creating the model is to design a new material handling system and analyze the necessary changes in the factory's layout, then verify the applicability and compatibility with the current state. The model was verified and validated based on the outcomes of real data that have been used as a reference compared to the obtained results of the simulation model. It is essential to clarify that the value of WIP and lead time of the plant would be the mean value of all variants. For the number of required AGVs, the optimization outcomes showed that it is possible to obtain the same desired results by using a lower number than the initial one, where the number of necessary vehicles has been minimized to 4 or even 3.

For the first scenario, to increase the demand by 100%, the most recognizable amendment could be noticed on the new value of lead time, where it declined due to the reason that the assembly times of the production lines were reduced to the half in order to get the throughput increased 100%. It is well known that the lead time is the time allotted for the production of a part on the line; however, in Facts Analyzer, the lead time is the time that one variant takes to pass through the entire model. Therefore, the plant's lead time went down by 39%, and this due to that assembly times form the most significant proportion of the total lead time and the transportation time, storage, loading, and unloading times form the residual proportion. It is evident that the magnitude of WIP is almost the same, and this small difference is because of the little variability in the model, which comes from the triangular distribution of transportation time and assembly time. The company required to have line-side buffers with a maximum and minimum capacity of 1- and 2-hours production respectively, the possible variability was not significant regarding the WIP.

As it concluded in the second scenario, to change the location of the material preparation area, the effects of changing the location of the supermarket on the model were marginal since it influenced only the lead time, which has been declined slightly. The reason that stands behind this little impact is related to the small portion of transportation time to the whole lead time of the plant. The new place of the parts store moved to the center of production lines, so the distance between the production lines changed, and this will affect the values of transportation times that AGVs need to pass before unloading material at the line-side buffers that located at the front of different lines.

The last scenario, to change the way by which AGVs deliver material to assembly lines, showed appreciable impacts on the designed model. The traveling kitting process found to be considered efficient on the material handling system since the plant's lead time declined significantly. As mentioned before, the safety stock of line-side buffers was decided to be equal to one-hour production, and the batch object is introduced to fulfill that condition, where it will maintain that safety percent of each limit proportion of different variants of all line-side buffers. Thus, when this level is about to be reached, AGVs will begin a new cycle loading the required number of kits regarding the needs at lines. In case of stationary kitting which is adapted in the basic model, an AGV serves only one workstation, and it waits until the total capacity being unloaded and for instance, if lines of small products require one kit for each of them, then two AGVs would move into assembly lines carrying the kits and the transportation time will be equal to the sum of the two lines together. In contrary, and if the same number of kits needs to be carried to the production lines, just one AGV will move handling kits to the lines under a transportation time that equals to the time of the most remote line which certainly is shorter than the previous transportation time in the stationary kitting process. Therefore, the lead time in the last scenario is substantially less than the lead time of the basic model.

During this study, some usual constraints that the modeler had to face when developing these kinds of projects can be mentioned. One of the main constraints is the lack of enough time of the stakeholders whom the system designer has to meet in order to develop the model. This means that continuous communication between the people in charge who are responsible for the real system and the developer of the simulation model is significantly necessary. The concerned company located in a remote city, so it was overworked to travel there and arrange kaizen workshops with stakeholders who were involved even though their little available time.

Another constraint was a model that is characterized by its stochastic nature. It is highly substantial to well-understand the objectives of any project and the most effective methods to follow in order to achieve them. Then the suitable simulation tools must be selected carefully for translating the conceptual model into a simulation one and implement the chosen method during the simulation method. The poor selection of the appropriate method and simulation tools will affect the whole process of system insight and will be a very tedious and time-consuming process. As it is mentioned previously, the discrete-event simulation such as this project contains a vast number of variables which are characterized by its stochastic behavior and this put an extra work on the designer to run a considerable number of experiments before reaching the steady-state at which the model begins to show an acceptable level of stability. The material handling system which is designed includes a set of random variables that are difficult to be predicted precisely during each cycle that AGVs do. For instance, the number of every product's parts throughout every individual cycle is one of those stochastic variables, and the difficulty of indicating them comes from the fact that the assembly lines determine the required quantities of each one depending on the needed process times to assemble the different product variants.

The last constraint is the lack of references that talk on the chosen simulation software used in this project, which is Facts Analyzer. The University of Skövde develops this software, so it is the only available resource to learn the software, and it is still in a continuous development process. Besides, it is not simple to implement some commands straight away because there is no direct option for those commands that could be selected. As well, inserting some decision variables is difficult to put in immediately. For instance, in the case of assigning the number of cycles, it is infeasible to consign this parameter in promptly way , and another way was followed to assign that parameter, and that way was to insert the number of entries that AGVs make at unloading stations when they disassemble empty boxes before starting a new cycle. However, after working to overcome these constraints, the model has been built, validated, and verified, and the results of the what-if scenarios and optimization obtained. The following chapter is Conclusions and Future Work.

7 Conclusions and Future Work

In this chapter, the methodology and results of this project are summarized. The accomplishment of different goals and the future work of this thesis is presented as well.

7.1 Conclusions

The case-related organization produces the manufacture of goods of different sizes, and it is located in the southern part of Sweden. The main objective in the performed study, as mentioned, was to design a new material handling system characterized by its efficiency and applicability in a future layout. Then determining the necessary number of transporting vehicles and run an optimization process by adapting one of the meta-heuristic algorithms in order to minimize the store capacity, LT, WIP, and evaluate some what-if scenarios regarding the MHS method. In this study, a lean and simulation-based optimization method, LeanSMO, has been selected to be the theoretical framework, and it showed to be very efficient since it combines the three approaches simulation, lean, and optimization.

Moreover, lean was used in this study, wherein several lean tools such as 5S, JIT, and Kanban were applied, and significant benefits were obtained. For example, Kanban, which represents one kind of pull system mechanism, helps to control the handling process of material effectively because Kanban assures that the material is transported under the JIT method. Beside Kanban, 5S was also applied in this project, especially in the material preparation area, and this tool has assisted in reducing the total lead time of the manufacturing company since it aided to standardize and sort the different types of kits that form products.

By analyzing the results of different scenarios, it is clear that the newly designed material handling system would have several beneficial impacts on the whole production process. The number of necessary vehicles has been reduced significantly after running the optimization as well as the plant's lead time has been decreased. Besides, the capacities of line-side buffers were reduced to an acceptable level that saves the space for the company and maintains the condition of one-hour production at the same time.

The development of this project and analyzing the different outcomes of "what-if" scenarios demonstrates that all objectives have been accomplished. The main objective was to design an efficient handling system which characterizes by its high applicability and effectiveness, then determine the required number of vehicles and minimize it by running multi-objective optimization algorithms, and this mission was done. The next primary objective was to minimize the capacities of line-side buffers, and this also done successfully. Some of the additional objectives were achieved, such as minimizing the capacities of part buffers and the length of conveyors.

Moreover, it could be said that the applied approach, which is Lean-SMO found to be efficacious and suitable in this project since the advantages of the three approaches could be obtained. This combination of the three approaches fits best this kind of study because one of its branches- which is the discrete event simulation- can follow the continuous changing of some parameters over the time as well as it is more suitable than a mathematical model that based on one kind of algorithm since the dynamic changing behavior of the system.

Finally, the concerned company has considered the results of this project as valuable knowledge for managers and stakeholders. The utilization of this knowledge is relevant for the implementation of the future vision strategy of the company regarding its forthcoming production, where new products will be introduced, and redistribution of the layout will be performed. Besides, a new internal logistic system will be implemented to gather the material from MPA and deliver it to assembly lines.

7.2 Future work

Future work could be the design of more scenarios that the company would be interested in to implement "what-if" experiments. For instance, one scenario could be to design a new material handling system with another type of transporters such as forklifts, tow trains, or overhead conveyors. After that, the final results could be compared against each other, and the best alternative could be discussed with the decision-makers and later on be implemented if they would approve of doing so.

In addition, another simulation software could be used in order to make the simulation process more manageable and to facilitate performing some commands that were difficult to be designed in the simulation software, which is the Facts analyzer. Flexsim simulation software is an advantageous choice to be selected in the future work of this study since it is more advanced than the Facts analyzer in the simulation part, and it gives more options to simulate different commands quickly and flexibly. Besides, the integration between the two simulation software tools could also be done, and for instance, the simulation model would be designed on Flexsim then import it to Facts analyzer to perform the optimization process using one of the meta-heuristic algorithms that are integrated with Facts. Hence, the most optimal configuration of the system could be found, and this would save significant amounts of money, time, and resources.

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9 Appendices

In this chapter, different project's assumptions, data included in the basic model, the entire figures of collected data, some outputs of the basic model, and some optimization results of the basic model are presented.

9.1 Appendix 1

This appendix shows the different assumptions of this project; they are included in the following table.

Assumption	Comments
One supermarket is available to serve the lines.	This helps in applying the kitting method, and all AGVs visit one storage area to load the required parts.
The traveling path, location of lines, and the supermarket on the shop floor are given.	This is agreed upon with the decision-makers, and it is the future layout for this study.
The storage capacity in each line is limited and known.	The maximum and minimum limits are known.
AGVs are only allowed to travel on predefined paths.	AGVs follow predetermined paths that are designed in the future plan, and this helps in calculating the transportation time of each AGV.
AGVs do not block each other during a cycle.	Two different ways were created for this purpose. Besides, the pull system -which is followed- contributes to this goal.
There are two AGVs' types, and they are identical in terms of loading capacity.	This is true for the basic model. However, for the third scenario, AGVs can be loaded with capacities varying from one to six kits.
All AGVs are similar in terms of speed.	This helps in calculating the transportation times of each products' type since the different distances are known.
Parts are supplied only in kits and only fully loaded, and empty kits are delivered and collected at each line, respectively.	This is true for the basic model. Nevertheless, for the third scenario, various capacities of kits to be loaded and empty kits are feasible.

Model assumptions

9.2 Appendix 2

This appendix presents different data included in the basic model for the entire entities.

Objects	Creation number/amount	Process time (sec)	Length of conveyors (m)	Buffers size (kits)	Loading time (sec)	Unloading time (sec)	Transportation time (sec)
Line_A_Product	2	-	-	-	-	-	-
Plastic_Boxes_Source	60	-	-	-	-	-	-
Line_B_Product_1	3	-	-	-	-	-	-
Line_B_Product_2	3	-	-	-	-	-	-
Line_B_Product_3	3	-	-	-	-	-	-
Line_C_Product_1	2	-	-	-	-	-	-
Line_C_Product_2	2	-	-	-	-	-	-
Pallets_Source	40	-	-	-	-	-	-
Line_D_Product_1	2	-	-	-	-	-	-
Line_D_Product_2	2	-	-	-	-	-	-
Kit_Preparation_Product_B_1	3	0	-	-	-	-	-
Kit_Preparation_Product_B_2	3	0	-	-	-	-	-
Kit_Preparation_Product_B_3	3	0	-	-	-	-	-
Kit_Preparation_Product_C_1	2	0	-	-	-	-	-
Kit_Preparation_Product_C_2	2	0	-	-	-	-	-
Kit_Preparation_Product_D_1	2	0	-	-	-	-	-
Kit_Preparation_Product_D_2	2	0	-	-	-	-	-
MPA_LineA	-	0	-	361	-	-	
Plastic_Boxes_Buffer	-	0	-	60	-	-	-
MPA_LineB	-	0	-	668	-	-	-
MPA_LineC	-	0	-	107	-	-	-

Objects	Creation number/amount	Process time (sec)	Length of conveyors (m)	Buffers size (kits)	Loading time (sec)	Unloading time (sec)	Transportation time (sec)
Pallets_Buffers	-	0	-	40	-	-	-
MPA_LineD	-	0	-	33	-	-	-
Kanban_A_1	-	0	-	-	-	-	-
Kanban_A_2	-	0	-	-	-	-	-
Kanban_B_1	-	0	-	-	-	-	-
Kanban_B_2	-	0	-	-	-	-	-
Kanban_B_3	-	0	-	-	-	-	-
Kanban_C_1	-	0	-	-	-	-	-
Kanban_C_2	-	0	-	-	-	-	-
Kanban_D_1	-	0	-	-	-	-	-
Kanban_D_2	-	0	-	-	-	-	-
Plastic_Boxes_Input	-	-	10	-	-	-	-
Pallets_Input	-	-	10	-	-	-	-
Disassembly_B	-	0	-	-	-	-	-
Disassembly_C	-	0	-	-	-	-	-
Disassembly_D	-	0	-	-	-	-	-
Boxes_A_Assembly	2	0	-	-	-	-	-
Boxes_B_Assembly	9	0	-	-	-	-	-
Boxes_C_Assembly	4	0	-	-	-	-	-
Boxes_D_Assembly	4	0	-	-	-	-	-
AGV_1_Source	6	-	-	-	-	-	-

Objects	Creation number/amount	Process time (sec)	Length of conveyors (m)	Buffers size (kits)	Loading time (sec)	Unloading time (sec)	Transportation time (sec)
Conveyor_A	-	-	10	-	-	-	-
Conveyor_B	-	-	10	-	-	-	-
Conveyor_C	-	-	10	-	-	-	-
Conveyor_D	-	-	10	-	-	-	-
Starting_Point_1	-	0	-	6	-	-	-
Starting_Point_2	-	0	-	6	-	-	-
Load_AGV_1_1	6	-	-	-	120	-	-
Load_AGV_2_1	6	-	-	-	120	-	-
Load_AGV_3_1	1	-	-	-	40	-	-
Load_AGV_4_1	1	-	-	-	40	-	-
Unload_AGV_1_2	-	-	-	-	-	120	-
Unload_AGV_2_2	-	-	-	-	-	120	-
Unload_AGV_3_2	-	-	-	-	-	40	-
Unload_AGV_4_2	-	-	-	-	-	40	-
OP_1_1	-	34	-	-	-	-	-
OP_1_2	-	34	-	-	-	-	-
OP_2_1	-	26.25	-	-	-	-	-
OP_2_2	-	33.75	-	-	-	-	-
OP_3_2	-	19	-	-	-	-	-
OP_3_1	-	19	-	-	-	-	-
OP_4_2	-	18.75	-	-	-	-	-

Objects	Creation number/amount	Process time (sec)	Length of conveyors (m)	Buffers size (kits)	Loading time (sec)	Unloading time (sec)	Transportation time (sec)
Unload_AGV_1_1	-	-	-	-	-	120	-
Unload_AGV_2_1	-	-	-	-	-	120	-
Unload_AGV_3_1	-	-	-	-	-	40	-
Unload_AGV_4_1	-	-	-	-	-	40	-
Load_AGV_1_2	6	-	-	-	120	-	-
Load_AGV_2_2	6	-	-	-	120	-	-
Load_AGV_3_2	1	-	-	-	40	-	-
Load_AGV_4_2	1	-	-	-	40	-	-
Empty_Boxes_A	-	0	-	6	-	-	-
Empty_Boxes_B	-	0	-	6	-	-	-
Empty_Boxes_C	-	0	-	5	-	-	-
Empty_Boxes_D	-	0	-	5	-	-	-
Store_1	-	0	-	55	-	-	-
Store_2	-	0	-	100	-	-	-
Store_3	-	0	-	16	-	-	-
Store_4	-	0	-	20	-	-	-
Assembly_A	-	-	-	-	263	-	-
Assembly_B_1_1	-	-	-	-	495.6	-	-
Assembly_B_2_1	-	-	-	-	846.6	-	-
Assembly_B_3_1	-	-	-	-	781.2	-	-
Assembly_C_1_1	-	-	-	-	1230	-	-

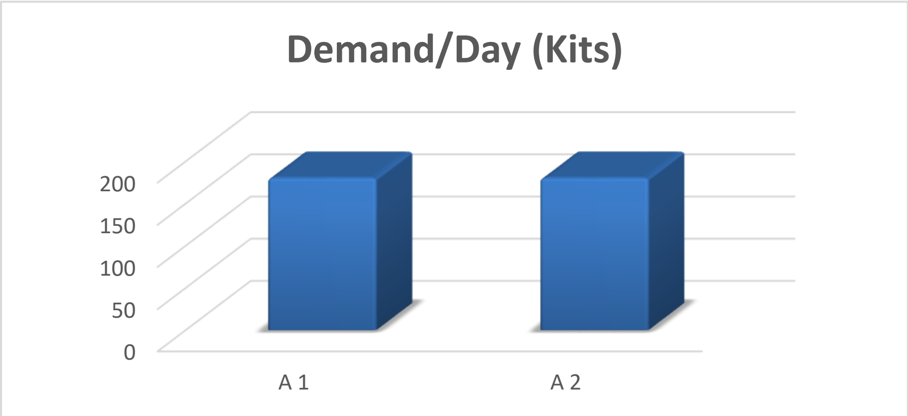
Objects	Creation number/amount	Process time (sec)	Length of conveyors (m)	Buffers size (kits)	Loading time (sec)	Unloading time (sec)	Transportation time (sec)
Assembly_D_1_1	-	-	-	-	4086.6	-	-
Assembly_D_2_1	-	-	-	-	12850.2	-	-
F_G_C	-	0	-	5	-	-	-
F_G_D	-	0	-	5	-	-	-
Sink_A	-	0	-	-	-	-	-
Sink_B	-	0	-	-	-	-	-
Sink_C	-	0	-	-	-	-	-
Sink_D	-	0	-	-	-	-	-

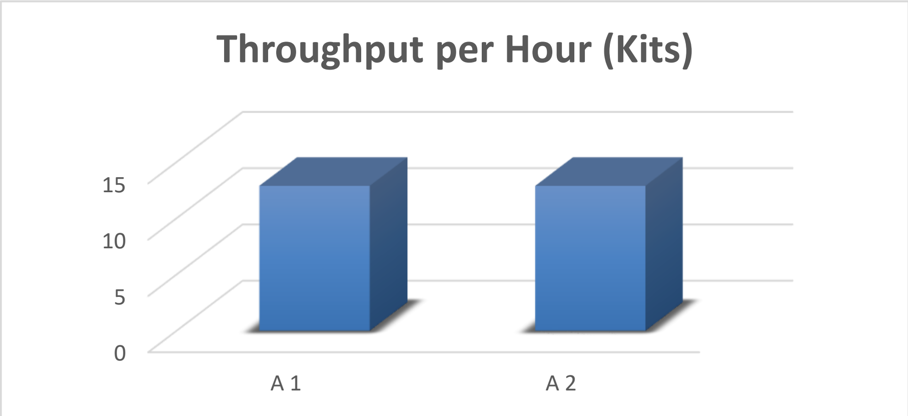
Data included in the basic model

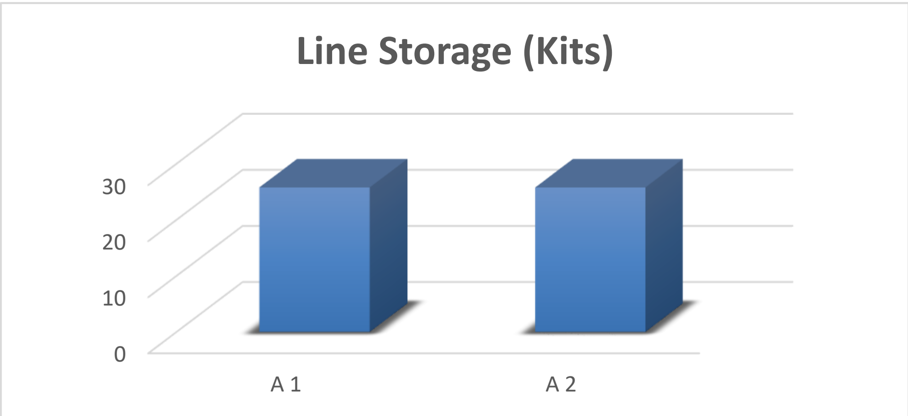
9.3 Appendix 3

In this appendix, the entire figures which represent the collected data for all production lines are presented.

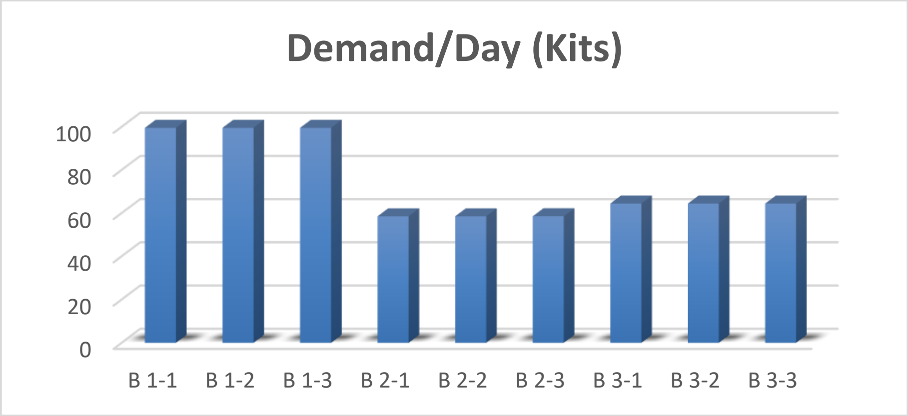
9.3.1 Line A data

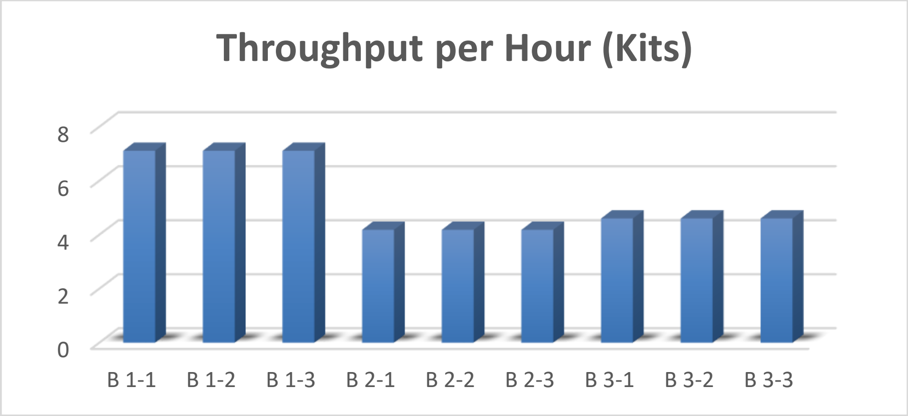


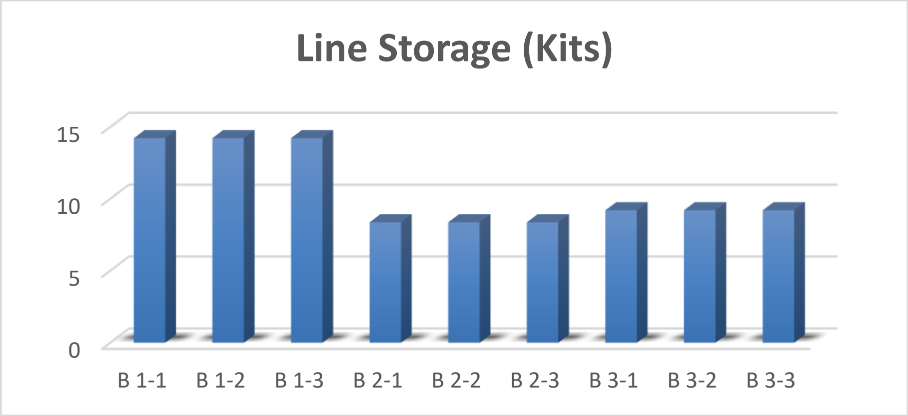




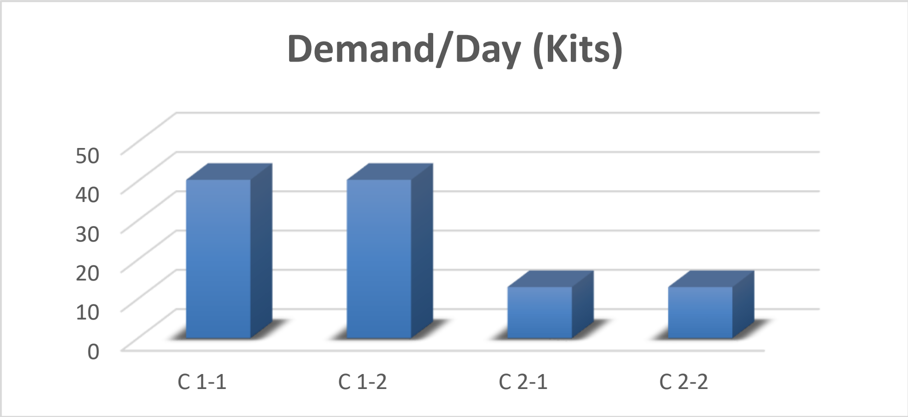
9.3.2 Line B data

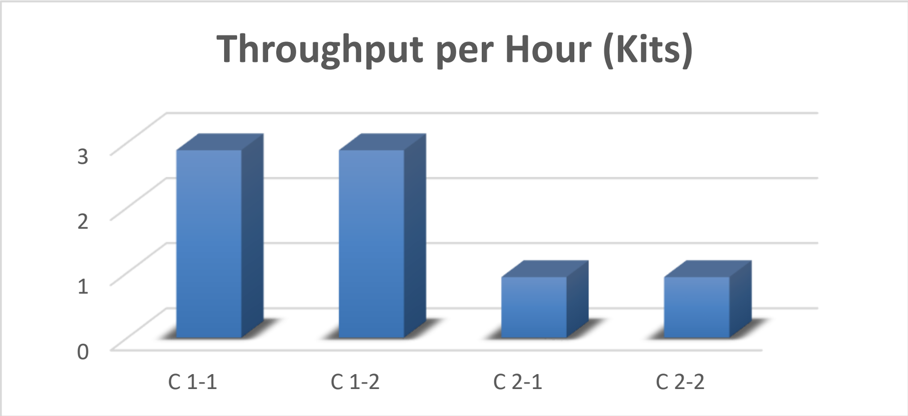


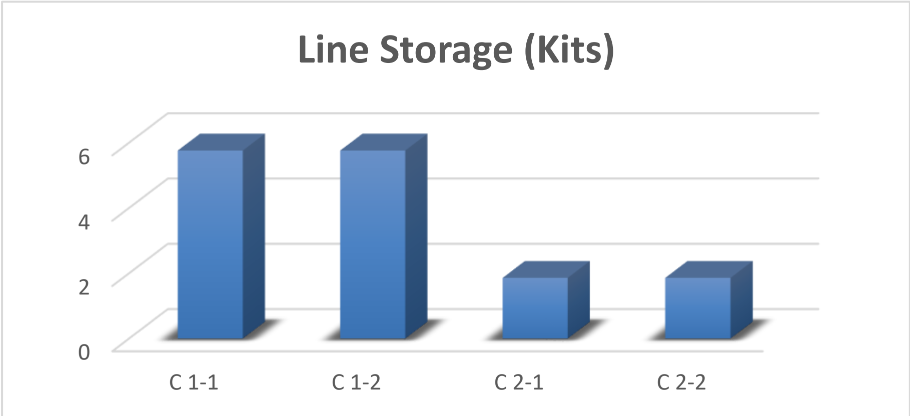




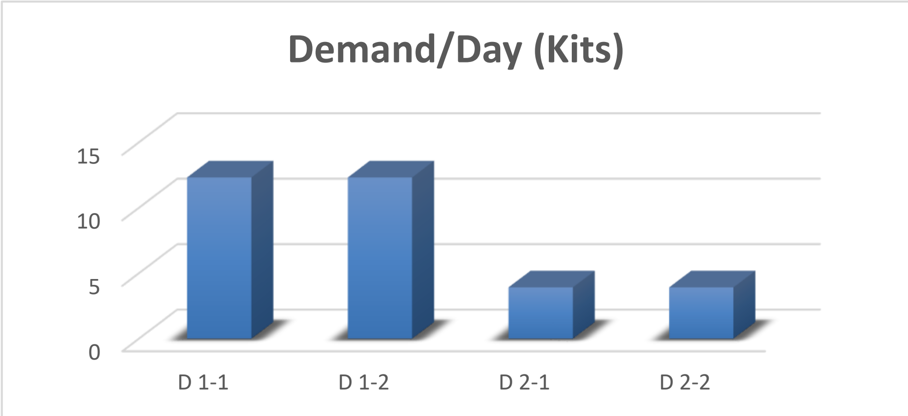
9.3.3 Line C data

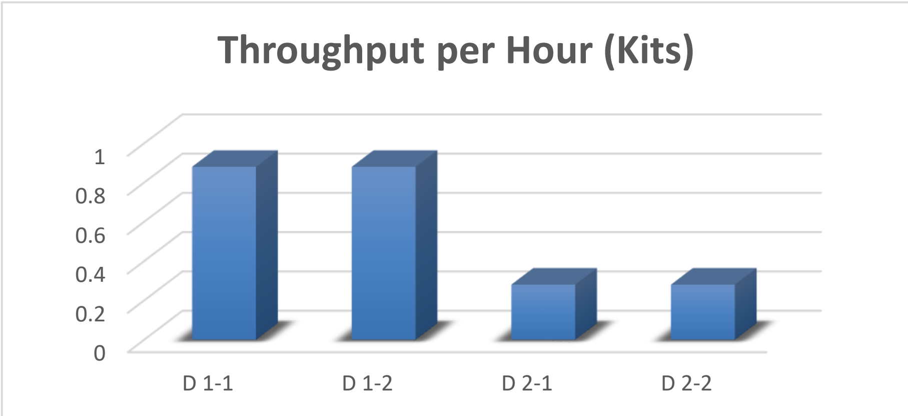


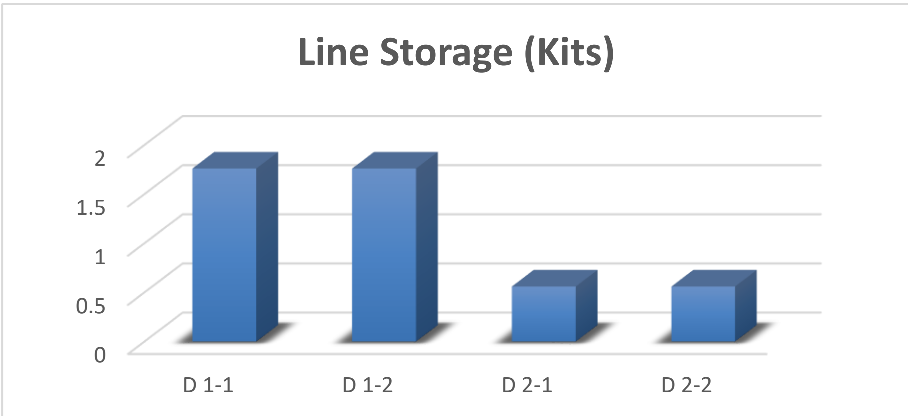




9.3.4 Line D data

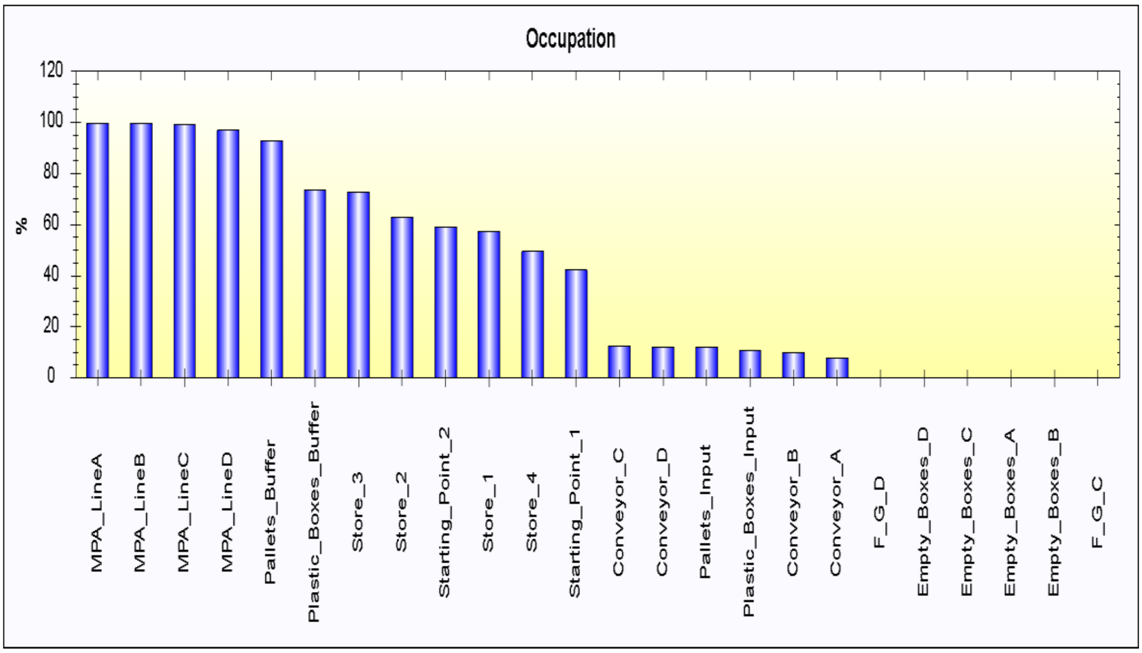


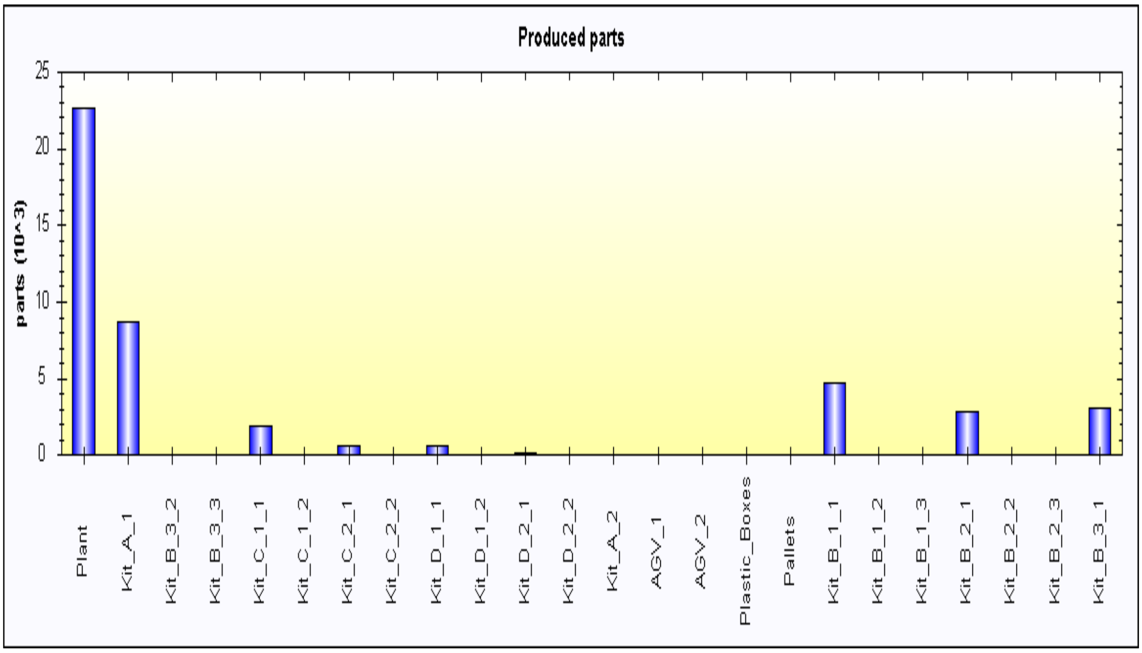


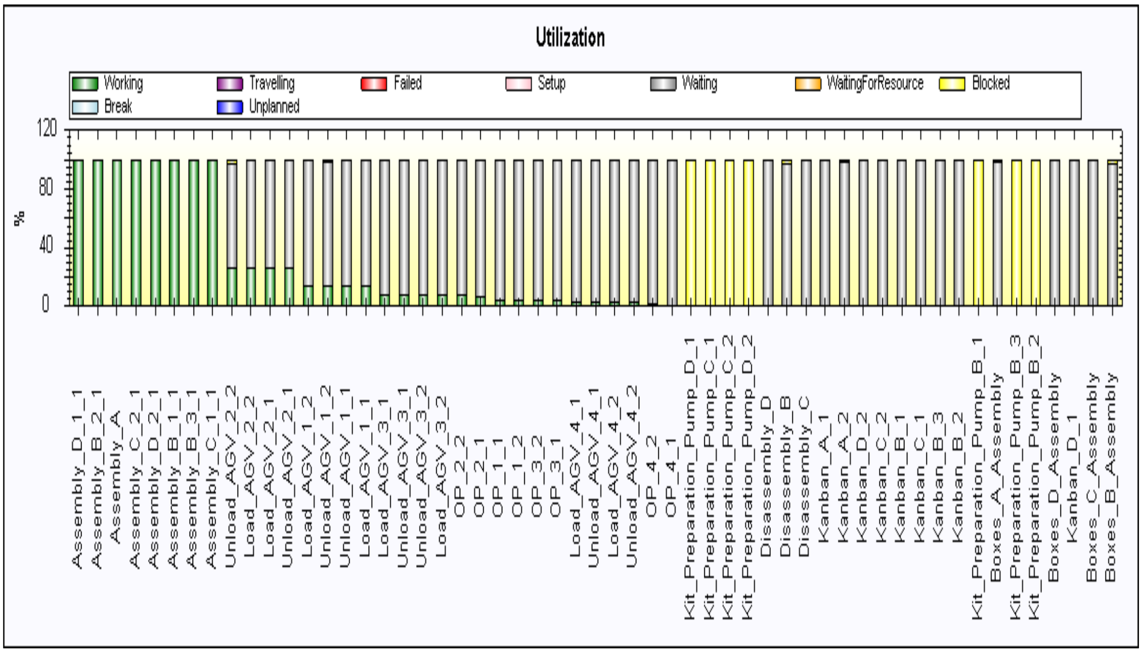


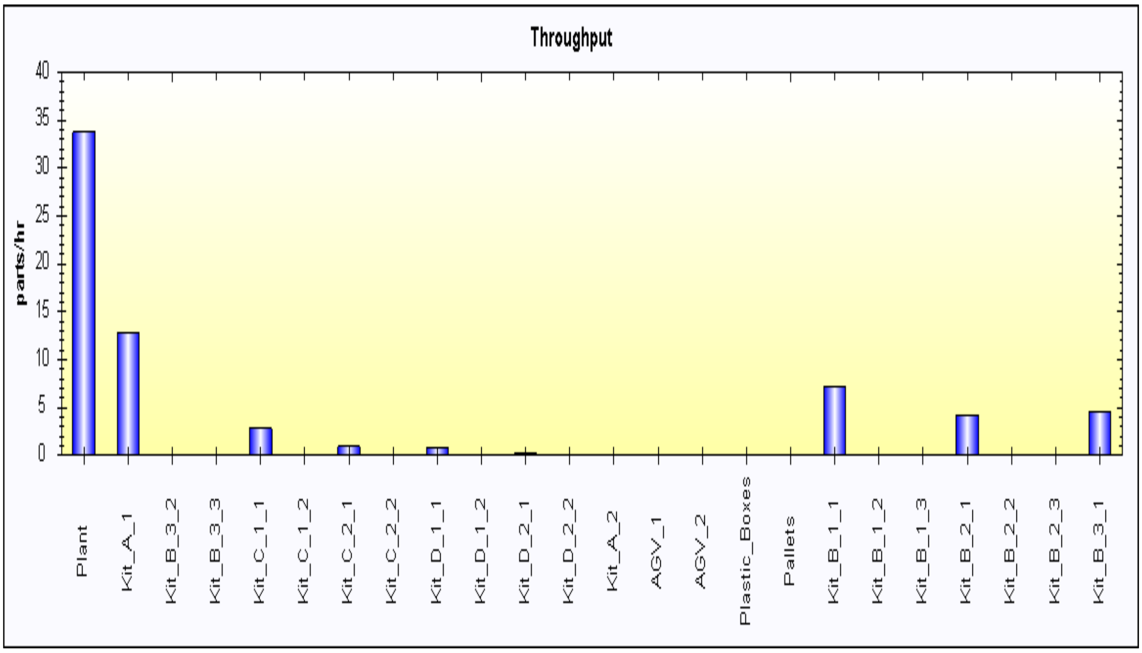
9.4 Appendix 4

In this appendix, some outputs of the basic model are presented.



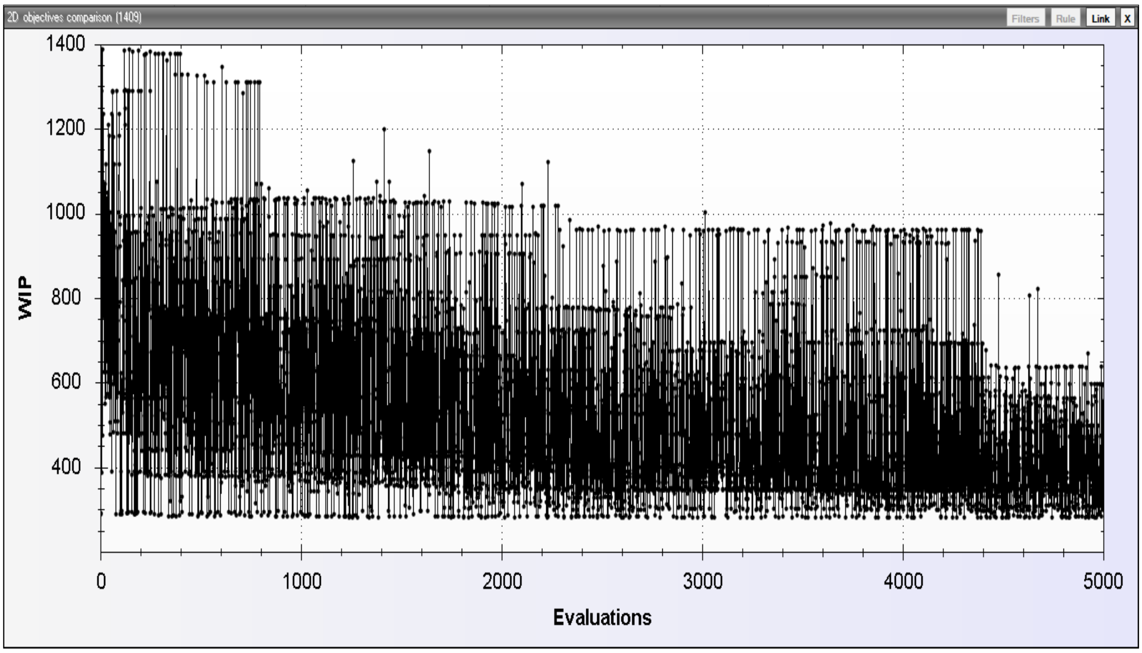


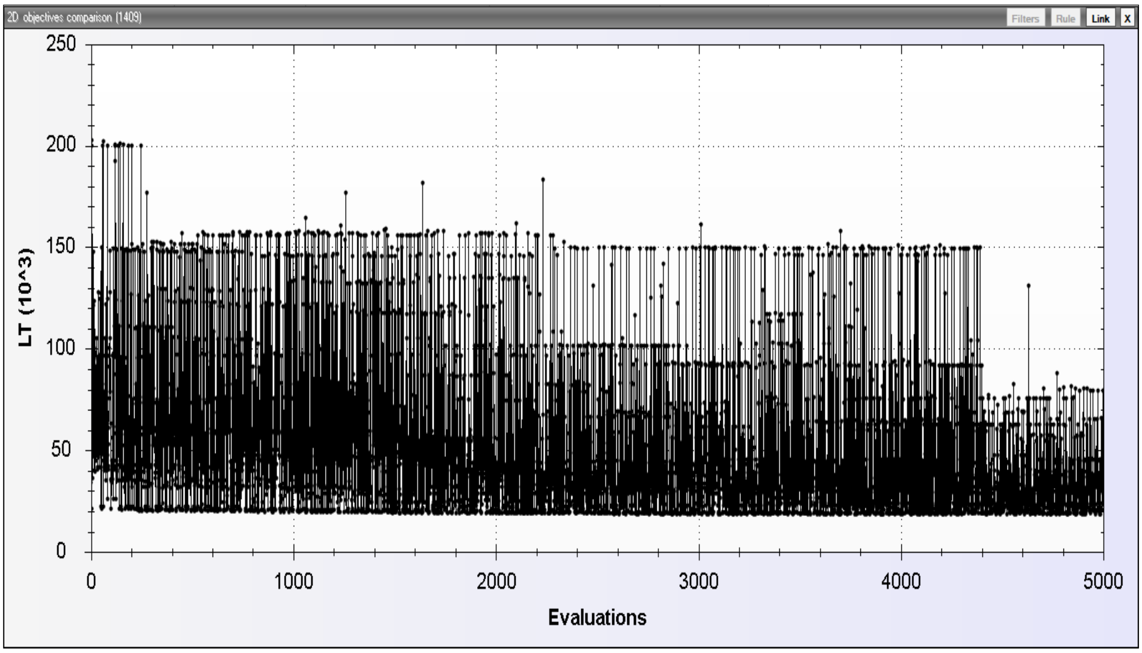

Utilization
Working
Travelling
Failed
Setup
Waiting
WaitingForResource
Blocked
Break
Unplanned
%
120
80
40
0

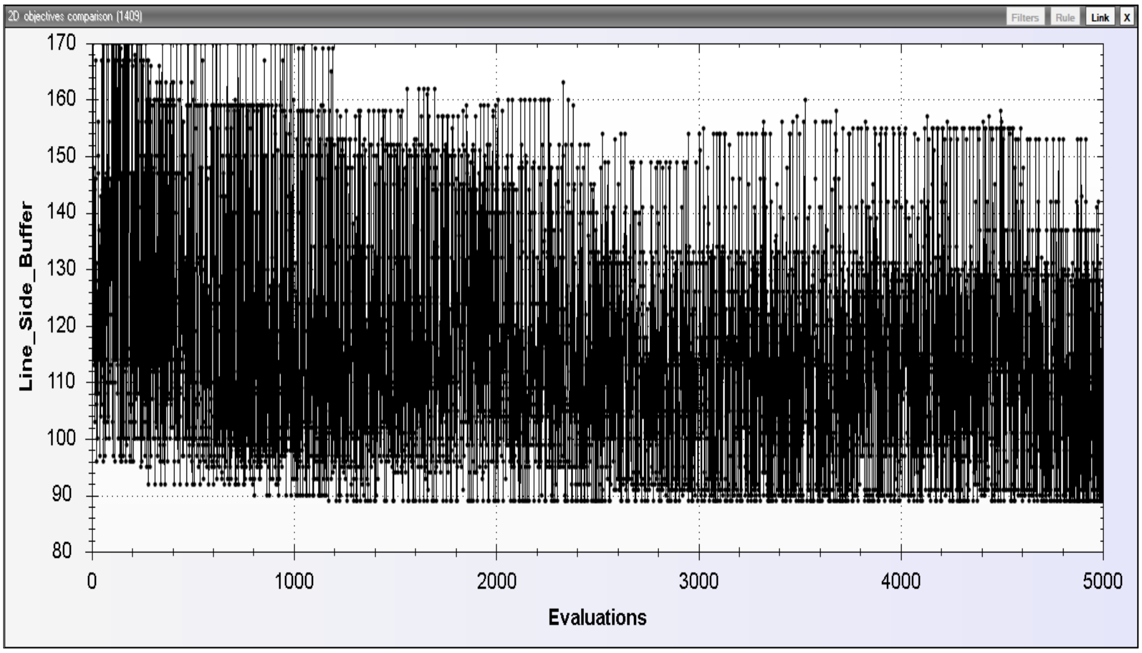

Throughput
parts/hr
40
35
30
25
20
15
10
5
0
Plant
Kit_A_1
Kit_B_3_2
Kit_B_3_3
Kit_C_1_1
Kit_C_1_2
Kit_C_2_1
Kit_C_2_2
Kit_D_1_1
Kit_D_1_2
Kit_D_2_1
Kit_D_2_2
Kit_A_2
AGV_1
AGV_2
Plastic_Boxes
Pallets
Kit_B_1_1
Kit_B_1_2
Kit_B_1_3
Kit_B_2_1
Kit_B_2_2
Kit_B_2_3
Kit_B_3_1

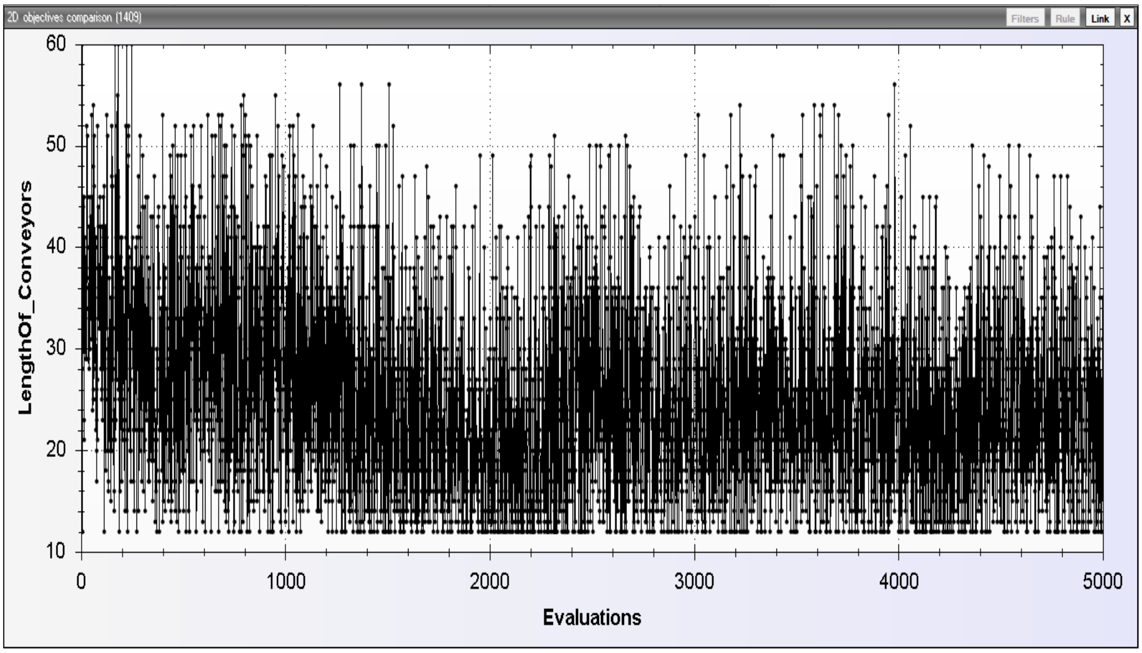
9.5 Appendix 5

This appendix includes some optimization results of the basic model.






2D objectives comparison (1409)
Filters
Rule
Link
X
Line_Side_Buffer
170
160
150
140
130
120
110
100
90
80
0
1000
2000
3000
4000
5000
Evaluations


2D objectives comparison (1409)
Filters
Rule
Link
X
LengthOf_Conveyors
60
50
40
30
20
10
0
1000
2000
3000
4000
5000
Evaluations