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UNIVERSIDADE D
COIMBRA

Mário Jorge Simões

Operational Research Models for Kitting Systems in the Warehouse of the Future

Dissertation in the context of the Master's Degree in Physics Engineering, supervised by Professor Telmo Miguel Pires Pinto and Professor Cristóvão Silva and presented to the Department of Physics of the Faculty of Sciences and Technology of the University of Coimbra.

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Modelos de Investigação Operacional para Sistemas de Kitting no Armazém do Futuro

Dissertação no âmbito do Mestrado em Engenharia Física, orientada pelo Professor Doutor Telmo Miguel Pires Pinto e pelo Professor Doutor Cristóvão Silva e apresentada ao Departamento de Física da Faculdade de Ciências e Tecnologia da Universidade de Coimbra.

Setembro de 2023

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"Success is the sum of small efforts, repeated day in and day out." - Robert Collier

Abstract

The potential of robotic systems in the kitting process for the automotive industry is relevant. It depends on certain conditions, such as the characteristics of the items being picked, the speed of the process (throughput), and the amount of space available. The production of a wide range of highly functional products with many variations (mass customization) has become more common in this industry, and the use of advanced technologies for warehouse operations (in the context of Industry 4.0) can provide several advantages to improve the kitting process. This dissertation examines the benefits and challenges of kitting systems and proposes innovative hybrid kitting strategies that can overcome these challenges. The main research questions associated with the design of automated and collaborative kitting operations are identified, the inherent operations are quantitatively modeled, and the operational research tools that can address these questions are defined. The layouts for the Asynchronous and Sequential Hybrid Kitting Systems are presented, and the Mixed Integer Programming models developed to allocate components to the robotic or collaborative kitting areas to minimize the total cycle time of the process are analyzed. Real-world and realistic data from an automotive manufacturer were used to assess the influence of several critical parameters. The results demonstrated that increasing picking errors leads to more components being allocated to the collaborative area and a longer cycle time. A considerable cycle time reduction occurs for the increase in simultaneous picking by operators. Different scenarios of component allocation were analyzed to understand the performance of the systems in terms of cycle time, showing that optimal assignment obtained by the models for both kitting systems resulted in lower total cycle times, with an advantage for the Sequential system. Furthermore, the relation between the energy consumption of AGVs and the kitting operations was addressed within an automated kitting area, showing the possibilities to minimize it through an Integer Programming model. With these contributions, industry decision-makers can easily opt for a kit preparation system to improve the quality of kit preparation with the Asynchronous system or a faster assembly line-like approach to perform kitting.

Keywords

Kitting; Line Feeding; Mixed-Model Assembly; Optimization; Mixed Integer Programming

Resumo

O potencial dos sistemas robóticos no processo de *kitting* para a indústria automóvel é relevante e depende de certas condições, tais como as características dos itens selecionados, a velocidade do processo e a quantidade de espaço disponível. A produção de uma ampla variedade de produtos altamente funcionais com muitas variações (personalização em massa) tornou-se mais comum nesta indústria e o uso de tecnologias avançadas para as operações num armazém (no contexto da Indústria 4.0) pode fornecer várias vantagens para melhorar o processo de preparação de *kits*. Esta dissertação examina os benefícios e desafios dos sistemas de *kitting* e propõe estratégias de *kitting* híbridas inovadoras que podem superar esses desafios. As principais questões de investigação associadas ao design de operações de *kitting* automatizadas e colaborativas são identificadas, as operações inerentes são modeladas quantitativamente e as ferramentas de investigação operacional que podem ser usadas para abordar essas questões são definidas. Os *layouts* para os Sistemas de *Kitting* Híbridos Assíncrono e Sequencial são apresentados e os modelos de Programação Inteira Mista desenvolvidos para alocar os componentes às áreas de *kitting* robótica e colaborativa, a fim de minimizar o tempo total do ciclo do processo, são analisados. Dados do mundo real e realistas de um fabricante de automóveis foram usados para avaliar a influência de vários parâmetros críticos. Os resultados demonstraram que o aumento de erros de *picking* leva a uma maior alocação de componentes para a área colaborativa e a um tempo de ciclo mais longo. Uma considerável redução no tempo de ciclo ocorre com o aumento do *picking* simultâneo por parte dos operadores. Diferentes cenários de alocação de componentes foram analisados para compreender o desempenho dos sistemas em termos de tempo de ciclo, mostrando que a atribuição ideal obtida pelos modelos para ambos os sistemas de *kitting* resultou em tempos de ciclo totais mais baixos, com uma vantagem para o sistema Sequencial. Além disso, a relação entre o consumo de energia dos AGVs e as operações de *kitting* foi investigada numa área de *kitting* automatizada, mostrando as possibilidades de minimizá-lo por meio de um modelo de Programação Inteira. Com estas contribuições, os decisores da indústria podem facilmente optar por um sistema de *kitting* para melhorar a qualidade da preparação de *kits* com o sistema Assíncrono ou por uma abordagem mais rápida, semelhante a uma linha de montagem, para a realização de *kitting*.

Palavras-Chave

Kitting; Abastecimento à Linha de Montagem; Montagem de Modelos Mistos; Otimização; Programação Inteira Mista

Contents

Acronyms

AGV Automated Guided Vehicle.

AHK Asynchronous Hybrid Kitting.

AMR Autonomous Mobile Robot.

API Application Programming Interface.

AS/RS Automated Storage/Retrieval System.

BoL Border of Line.

BOM Bill of Materials.

EP End Product.

FCFS First Come, First Served.

IDE Integrated Development Environment.

IIoT Industrial Internet of Things.

MIP Mixed Integer Programming.

OEE Overall Equipment Effectiveness.

OEM Original Equipment Manufacturer.

OPS Order Picking System.

SHK Sequential Hybrid Kitting.

SKU Stock Keeping Unit.

WIP Work-In-Progress.

WoF Warehouse of the Future.

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Chapter 1

Introduction

This dissertation presents a study on operational research models and tools in the warehouse of the future context. The purpose of this chapter is to provide an overview of the work undertaken, clearly defining the problem that this research aims to address, providing the necessary background context [1.1] and motivation [1.2] for the research to understand the importance of the problem and the potential impact of this work. The objectives [1.3] that were set and the structure [1.4] of this master's dissertation are also presented in this chapter.

1.1 Context

The automotive industry plays a crucial role in the economic growth of the European Union (EU) and, according to the latest data from the European Association of Automobile Manufacturers (ACEA, 2022a), it has generated 14.6 million jobs in the EU, which represents approximately 6.7% of total EU employment. The industry has also produced 18.5 million cars, accounting for about 20% of global production, making Europe the second largest producer in the world (Figure 1.1).

Given the high investment and innovation capacity of other regions and significantly lower labor costs, it is essential for the third largest transformative industry in Portugal to initiate projects and initiatives that accelerate innovation and technological progress in the sector (ACEA, 2022b). This will ensure the maintenance of production levels and the pace of the automotive industry, as well as the safety of workers, to mitigate the impact of increasing challenges in the industry, such as the COVID-19 pandemic. According to the Portuguese Automobile Association (ACAP), the pandemic resulted in a 28% reduction in automobile production in Portugal from January to September 2020 compared to the same period the previous year (ACAP, 2022).

Therefore, it is essential that European Original Equipment Manufacturers (OEMs) maintain the productivity and competitiveness of their factories by ensuring high standards of quality and excellence, as well as the ability to customize mass production ("mass customization"). This is only possible when operating in a smart, flexible, and connected factory context.

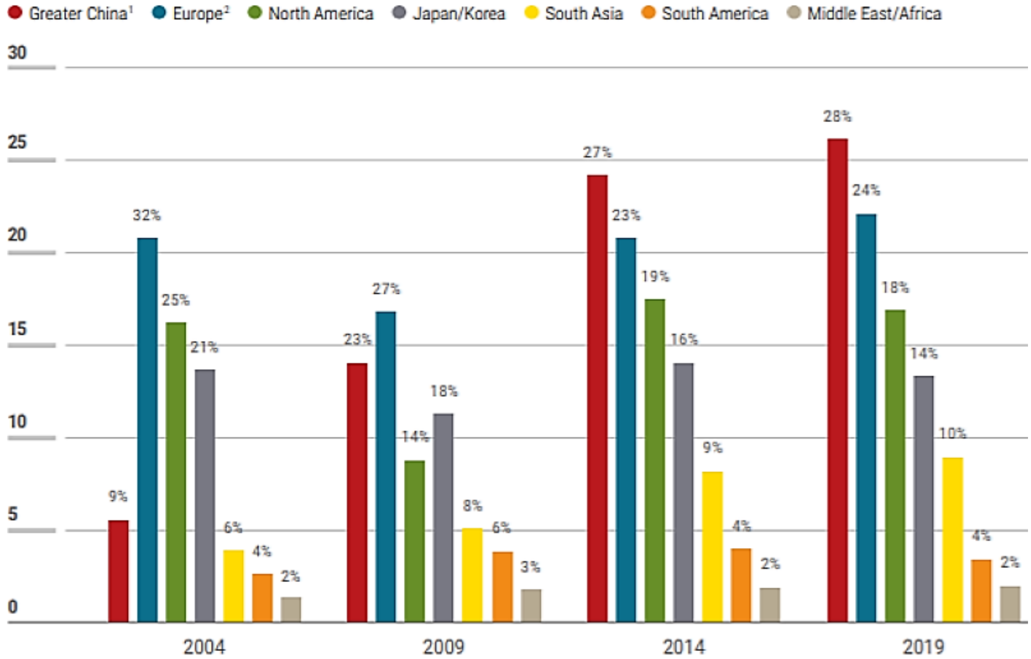


Figure 1.1: Global automobile production evolution between 2004 and 2019.

The concept of smart factories, which is associated with the fourth industrial revolution, involves flexible production ecosystems that allow automation of their inherent processes and the ability to self-adapt and learn in real-time based on the convergence of information and communication technologies. A consortium comprising complementary skills and expertise from the business entities, as well as innovation and research system entities, has developed the ***Warehouse of the Future (WoF)*** project to address various convergence technological aspects for the warehouse of the future. The project WoF aims to develop innovative, flexible and efficient processes and methodologies to automate the picking, kitting and material/component handling processes in the industrial context of the factory floor of a car manufacturing company, located in Portugal.

1.2 Motivation

As the era of mass customization has arrived, the automotive industry has struggled with the exponential increase in the complexity of logistics and intralogistics processes in the context of a smart warehouse, leading OEMs to adapt their factories and increasingly optimize their material supply systems for assembly lines (Brabazon et al., 2010). In this context, based on the concentration of added value on the production line, the kitting process has become increasingly relevant in the automotive production industry. Kitting involves the unique and heterogeneous grouping of various components/parts into a specific structure (a "kit") that will meet the needs of one or more assembly operations for a particular vehicle.

Although the automotive industry is one of the most advanced in the field of robotics, with a strong tradition in production automation (Buntak et al., 2019), picking and kitting processes are still predominantly carried out by operators, which has three considerable consequences:

- Higher margins of error, resulting in constraints on production lines;
- Lack of information to understand and remedy the failure, decreasing the operational efficiency;
- Increased risk of injury to the operators involved in this operation and dependence on the variability associated with the human labor.

The limited automation of picking and kitting processes is mainly due to (i) the complexity underlying a broad and diverse range of possible combinations of components/parts due to the increasing trend of mass customization in automotive production, (ii) the high diversity of parts/components (and their suppliers) in each industrial unit, and (iii) the complexity and variability of the characteristics of the parts to be handled and included in the kits, due to their geometric shapes, physical-mechanical characteristics, among others (Polydoros et al., 2016).

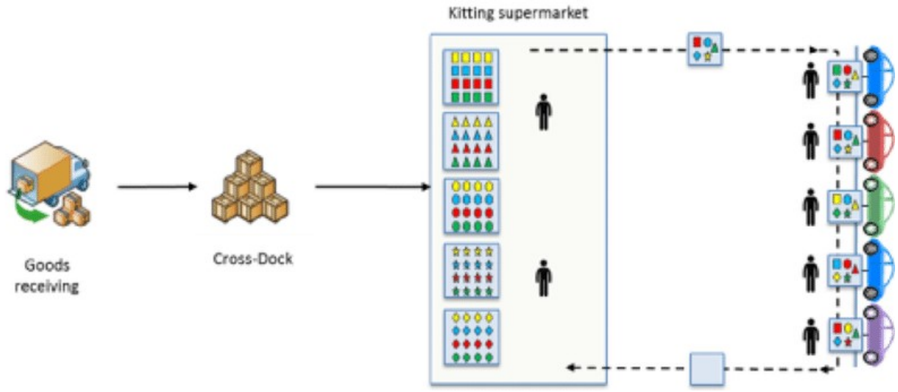


Figure 1.2: Illustrative diagram of the picking and kitting process (Krueger et al., 2019).

Given the current impossibility of fully automating picking and kitting processes in the automotive production context, it becomes critical to conduct an efficient process mapping study of the operations capable of automation, as well as to define new strategic approaches or technological solutions that can streamline the most complex processes and thus provide significant gains in terms of productivity and competitiveness on the factory floor, freeing up operators for more demanding and higher value-added tasks.

Moreover, the need to explore ways to minimize energy consumption, particularly in the context of AGVs, which are becoming more and more widely applied in the industrial companies responsible for transporting components, becomes paramount in the kitting process. As the manufacturing landscape seeks greater sustainability, investigating methods to optimize energy usage in tandem with process enhancement can lead to a more holistic and ecologically responsible production environment (Qiu et al., 2015).

1.3 Objectives

The main objective of this dissertation project is to study and develop operational research techniques with a focus on the following objectives:

- A comprehensive analysis of the existing designs and implementations of kitting strategies and the creation of innovative layout concepts for modern warehouses, identifying and organizing kitting areas, categorizing, and clustering various types of parts and components;
- The development and characterization of the operations included in the cycle time correspondent to the kitting process, analyzing how the tasks should be considered and quantified for this study;
- The investigation and development of mathematical programming models, hybridization strategies, and optimization-simulation techniques to handle large-scale instances;
- The compilation of datasets based on the technical information and realistic data collected from picking and kitting activities and specialists in the different kitting processes;
- The study of the potential of kitting systems to support time and energy-efficient kit preparation when the picking task is performed robotically;
- The critical analysis of the layouts and models developed in efficiency terms and feasibility to be implemented in a real environment.

1.4 Structure of the Document

This document is divided into the following chapters:

- **State of the Art (Chapter 2)** - This chapter aims to provide an overview of the current state of research in the field of operational investigation. In this chapter, the literature related to this topic is analyzed, and the current algorithms that have been developed are explored. This chapter aims to understand the current state of the field and identify any gaps in the existing research that my work can address.
- **Methodology (Chapter 3)** - This chapter provides a detailed description of the innovative layouts of hybrid kitting systems developed, with all the components and processes associated characterized as well as the operational research methods with the mathematical formulation and techniques used in this research, including the assumptions and limitations of each method.

- **Results and Discussion (Chapter 4)** - Chapter 4 presents the results of applying the models developed to realistic and real-world data/case study, providing a detailed analysis of the results and discussing their implications.
- **Energy Consumption of AGVs in Robotic Kitting (Chapter 5)** - The fifth chapter presents an Integer Programming model developed with the goal of minimizing the energy consumption of AGVs in the kitting process, enhancing operational efficiency while ensuring accurate kit assembly.
- **Conclusion (Chapter 6)** - In this final chapter, a concise and comprehensive summary of the main findings and contributions of this research is provided, presenting the contributions of the work and future directions that research should take in other to improve kitting strategies in modern warehouses.

Chapter 2

State of the Art

This chapter aims to present the state of the art, focusing on kitting activities in modern warehouses, presented models and heuristics that can relate to the scope of this project, selected according to a set of criteria established between the author and the supervisors.

First, key findings on line feeding policies are highlighted, and the existing literature is reviewed on the kitting and picking processes, explaining the main definitions and considerations proposed, where the use of advanced technologies and approaches for warehouse operations characterizes the current trend of Industry 4.0. The order picking systems (OPSs) and all the technological options proposed to partially or fully automate the process are also reviewed as the performance metrics to evaluate the efficiency and effectiveness are presented. The different kitting system types considered in the literature and the kitting planning and costing models used in previous research are analyzed to provide a better understanding base for this dissertation, opting for the adequate kitting system configuration to apply in an automotive industry context.

2.1 Assembly Line Feeding Policies

In the domain of manufacturing and assembly line operations, the strategy of parts feeding plays a pivotal role in maintaining a smooth and efficient workflow. Different approaches presented in the literature have been designed to ensure that the right components are available at the right time and in the right quantities for assembly processes. These policies encompass different methods, each tailored to distinct production scenarios. Four primary types of assembly line feeding policies are:

- **Line Stocking**: In the line stocking approach, considered one of the simplest policies of line feeding, the components in a complete pallet or box are directly delivered from the storage area to the positioned at the Border of Line (BoL). This strategy is advantageous when there is a high degree of predictability in component usage as well as higher demand for the same components, as it minimizes delays associated with fetching parts from remote storage areas, reducing the need to handle components except for the transportation (Battini et al., 2015).

- **Boxed-Supply**: In a boxed-supply line feeding policy, the components stored in pallets or containers are prepared, being repackaged to be supplied in smaller boxes to the BoL, where they are stored until depletion, noting that these boxes are filled with homogenous parts. This policy is similar to the line stocking with the addiction of transportation from the warehouse to the preparation area and repackaging processes (Schmid and Limère, 2019).
- **Sequencing**: Sequencing policy focuses on delivering components to the assembly line in a predetermined sequence in the case of space restrictions when having an increasing number of part variants required in the BoL. In this method, the different part variants stored in pallets or containers are transported to a preparation area, where the variants are sorted following a demand sequence into a box. After that, the boxes with the sequenced parts are transported and stored in the BoL until depletion (Sali et al., 2015).
- **Kitting**: Kitting represents a sophisticated approach in which all the multiple components and variants required at the BoL in a specific workstation are bundled together into kits. The process involves retrieving the different components to be transported and stored in a preparation area. In this preparation area, the different parts are repackaged into a kit, being then transported to the BoL, where all parts of the kit are used and depleted in one product (Schmid and Limère, 2019).

Within the context of this dissertation, particular emphasis will be placed on evaluating the kitting-based line feeding policy, given its potential to employ the benefits of automation within the Industry 4.0 domain and standing to enhance the effectiveness of assembly line operations.

2.2 Kitting and Picking processes

Kitting and picking processes are essential for warehouse operations, particularly in the automotive industry, where producing a wide range of highly functional products with many variations (mass customization) has become a norm. This reality can be reached by operating in a smart factory context, flexible and connected. According to a study by the Capgemini Research Institute, conversion to smart facilities has the potential to generate significant productivity improvement, improved Overall Equipment Effectiveness (OEE) and reduced stocks and Work-In-Progress (WIP) (Capgemini, 2020). This section provides an overview of the current state-of-the-art kitting and picking processes, their framing, and their application in the automotive industry.

The kitting and picking processes are integral parts of the logistics operations in the industry. They involve selecting, preparing, and delivering the necessary parts and components to assemble medium to complex products (Brynzér and

Johansson, 1995). Researchers in the fields of logistics, supply chain management, production planning, and operational research have been studying these processes for several years (Sellers and Nof (1987); Bozer and McGinnis (1992); Caputo et al. (2015b)).

The picking process is an essential aspect of logistics operations in the automotive industry. The process involves selecting and collecting the parts and components in the warehouse needed for vehicle assembly (Figure 2.1). It aims to ensure that the parts and components required in the assembly line are picked correctly at the right time and in the required quantity. Using advanced technologies like robots and automated storage and retrieval systems, the picking process can be highly automated (Jaghbeer et al., 2020).

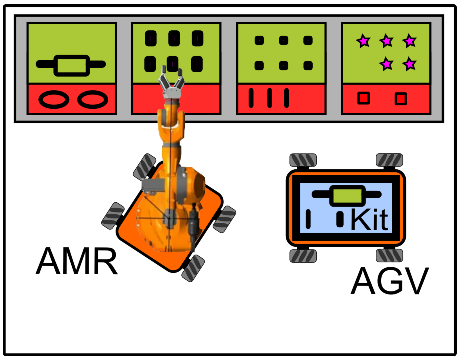


Figure 2.1: Schematic representation of an Autonomous Mobile Robot (AMR) picking a component from a shelf.

In the literature, the kitting process has been defined as a method of organizing and grouping different components and parts in a specific kit (Figure 2.2), which will then be used for a particular purpose or sent to a specific location. In the automotive industry, kitting is used to assemble vehicles, where components are assembled in a particular order and according to a specific set of instructions. Kitting aims to reduce the number of times an item needs to be handled, thereby reducing the overall cost and increasing efficiency compared to different supply policies (Caputo et al., 2021).

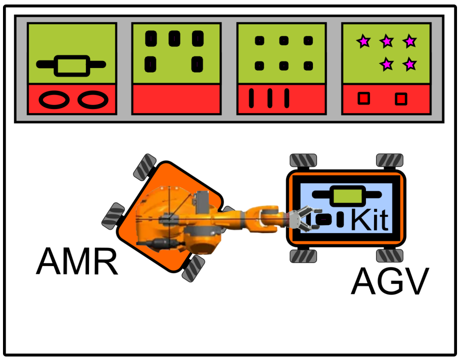


Figure 2.2: Schematic representation of an AMR performing the kitting process.

Recent research has shown that using automation and robotics in the kitting and picking processes can significantly improve efficiency and reduce costs in the automotive industry. For example, a study by Boysen et al. (2017) found that using robots for kitting in the automotive industry can significantly reduce labor costs and increase efficiency. Another study by Caputo et al. (2018) found that the use of automation in retrieval kitting systems processes can lead to a significant reduction in effective costs and an increase in productivity.

In addition to automation and robotics, other advanced technologies, such as supervised and unsupervised learning, are also used to improve kitting and picking processes. Fager et al. (2021a) found that using supervised and unsupervised learning in vision-guided robotic bin-picking applications can enhance the quality of recognition and inventory management in kitting processes, reducing costs and improving efficiency. A benefit of such an approach is higher resource flexibility and an overall increase in efficiency because the operator and robots can work better in parallel.

In automotive warehouse operations, picking and kitting systems play a vital role. Recent research has shown that automation, robotics, and machine learning can significantly improve efficiency and reduce costs in these processes. As AMRs are currently being introduced in many intralogistics operations, that can communicate and negotiate with several resources in the warehouse, such as other machines, devices, Automated Guided Vehicles (AGVs), or systems, independently, decentralizing the decision-making process (Fragapane et al., 2021).

2.3 Advanced Technologies in Warehouse Operations

The current trend in the manufacturing sector is referred to as Industry 4.0. This transformation is characterized by integrating advanced digital technologies into production processes. These technologies include cloud computing, self-driving systems, human-friendly robotics, computer vision, augmented reality, deep learning algorithms, 3D printing, intelligent sensors, and the integration of devices and machines through the Industrial Internet of Things (IIoT) (Cohen et al., 2019).

The incorporation of advanced technologies into warehouse operations has the potential to significantly improve efficiency and cost-effectiveness (Wang et al., 2016). Autonomous or collaborative robots and drones, for instance, can streamline the order-picking process and the majority of the factory operations, enabling orders to be fulfilled more quickly and accurately than if done manually (Žulj et al., 2022). Additionally, the implementation of computer vision and deep learning algorithms can enable machines to quickly identify and locate items within the warehouse, reducing the amount of time spent searching for products (Fager et al., 2021a) and drastically minimizing the time needed for motion planning, through real-time pallet and initial part detection, and pre-computing trajectories (Holz et al., 2015).

In addition to these technologies, integrating the Industrial Internet of Things (IIoT) can bring about new levels of connectivity and data-driven decision-making (Cohen et al., 2019). With sensors and other data-gathering devices installed throughout the warehouse, it is possible to collect real-time information about the status of their operations and make data-driven decisions to optimize processes and reduce downtime, reducing the time needed to complete kitting tasks in a "real world" scenario (Tung et al., 2022).

Furthermore, 3D printing and additive manufacturing can revolutionize how products are manufactured and distributed, reducing the need for extensive inventories and enabling businesses to respond quickly to changing customer demands (Gaub, 2016).

Accordingly to Hanson and Brolin (2013), kitting is a well-known strategy for managing materials in assembly systems, which has many advantages over traditional continuous supply methods. However, one of the main drawbacks of kitting is the high resource consumption required to prepare kits, which includes the selection and organization of components in kits. The implementation of automation technology has the potential to significantly decrease the reliance on manual labor and subsequently reduce operational costs. Furthermore, the process of kit preparation, which includes the selection and organization of components, is often associated with concerns related to ergonomics and quality (Hanson et al., 2018).

2.4 Order Picking Systems (OPSs)

Order picking is an essential aspect of the supply chain and greatly impacts the success of different enterprises. Despite manual order picking by human laborers still being prevalent in many organizations, many technological alternatives are emerging to fully automate the process or support human order pickers.

Order picking, an essential aspect of warehouse operations in the industry, accounts for approximately 55% of these operations time (Bartholdi and Hackman, 2019). It involves retrieving products from storage to fulfill customer orders. It is considered one of the most labor-intensive activities within a warehouse, and it can be separated into different tasks shown in Table 2.1.

Table 2.1: Tasks related to the Order Picking process (Bartholdi and Hackman, 2019).

Activity	**Order-picking time**
Traveling	55 %
Searching	15 %
Extracting	10 %
Paperwork and other activities	20 %

Analyzing the Table 2.1, the most considerable portion of the cost of order picking is due to the travel time involved. Therefore, order picking is a costly operation within a warehouse. The focus of designing a Order Picking System (OPS) is to minimize this time that isn't productive.

2.4.1 Classification of OPSs

This section presents a classification of OPSs for examination in this dissertation, which is based on a highly cited article by Jaghbeer et al. (2020). This categorization distinguishes OPS based on using a human operator, a robot, or no picker in performing the picking task, as illustrated in Figure 2.3.

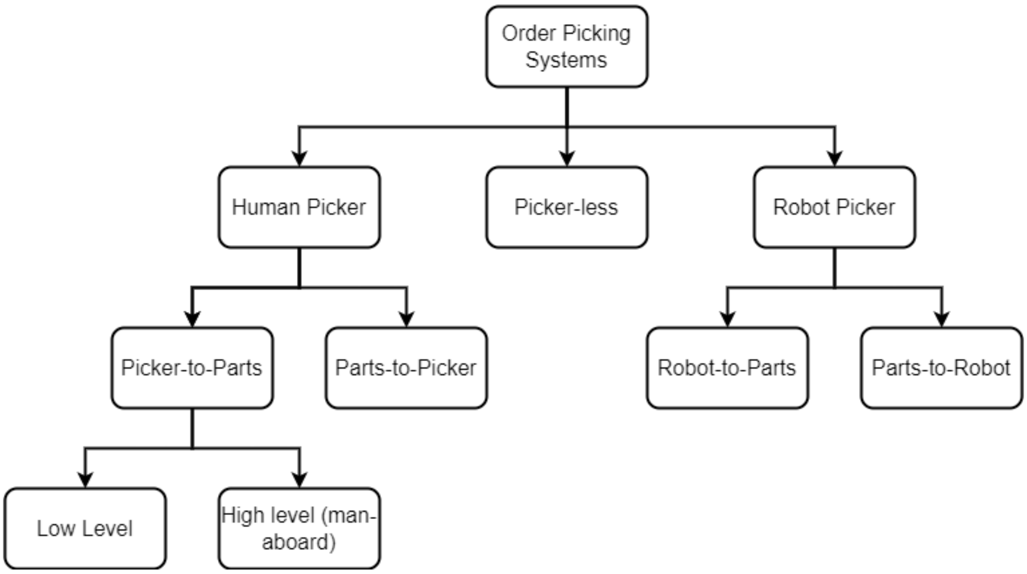


Figure 2.3: Diagram containing the different OPS considered (adapted from Jaghbeer et al. (2020)).

Human Picking Systems

Human picking refers to the process of manually selecting and picking items, such as parts or components, from a storage area and preparing them for use or further processing (Brynzér and Johansson, 1995). This is performed by a human worker who physically moves to the storage area, selects the items to be picked, and moves them to a location where they will be kitted, packaged if necessary, and processed to the assembly line. Human picking is commonly used in many different types of operations, including in warehousing and internal distribution within the factory. While human picking is a labor-intensive process, it is often necessary due to the flexibility and adaptability of human workers, who can handle a wide range of items, shapes, and sizes, which can correlate with a large group of items in the automotive manufacturing industry. This category of human picking can be further divided into two classifications: Picker-to-Parts and Parts-to-Picker.

According to Tompkins et al. (2010), human OPS includes preparation, searching for items, traveling to different locations, and picking items from their storage places.

- In ***Picker-to-parts***, which is widely used, the order picker physically travels down the aisles to collect items, getting information on the quantity and the order of the items to be retrieved, either on a paper pick list or an electrical device (Grosse et al., 2017). This method can be further categorized into low-level and high-level order picking.

  - In **low-level order picking**, the order picker retrieves the items from storage racks or bins as they walk down the storage aisles.
  - **High-level (or man-aboard) order picking** involves using high storage racks and employing a lifting order-pick truck or crane, upon which the order picker travels to reach the designated pick location. Upon arrival, the crane halts automatically in front of the required location, and the order picker subsequently collects the items.

- In a ***Parts-to-picker*** system, the required items are retrieved from storage using Automated Storage/Retrieval System (AS/RS) such as aisle-bound cranes, steady conveyors, carousels, or AGVs, and brought to a central depot for picking. The order picker at the central depot selects and packs the required items while the remaining load is returned to storage. This system is sometimes referred to as a unit-load or end-of-aisle order-picking system. It is characterized by reduced human activities, limited to picking and packing tasks.

Robot Picking Systems

Robotic picking systems, presented in the right branch of the diagram in Figure 2.3, are automated OPS that use robots to retrieve and pick items from storage locations in the warehouse and deliver them to a designated pick position. These systems are designed to reduce the manual labor involved in order picking, which is more expensive in the long term than with robots, and improve the efficiency and accuracy of the process (Lamballais et al., 2017). They typically employ sensory equipment, machine learning algorithms, and advanced robotic technologies to identify and retrieve items from storage areas and convey them to the designated pick location (Lamballais Tessensohn et al., 2020). In contrast to manual order picking systems, which rely on human workers to perform the entire process, robotic picking systems automate specific steps, such as search and travel, and leave only the picking and packing steps to be performed by human workers.

The categorization of OPSs using a robotic picker involves two types, namely "robot-to-parts" and "parts-to-robot", which differ based on the location at which the robot performs the act of picking, as noted in Jaghbeer et al. (2020).

- In a ***Robot-to-Parts*** OPS, it is similar to the *picker-to-parts* presented in the previous subsection (2.4.1), with the difference that here actual robots move through the storage areas and pick up the respective items (Jaghbeer et al., 2020). This can be achieved with AGVs carrying robots, normally designated by AMRs or mobots. Navigating through the warehouse and picking items, these robots reduce the need for manual labor and increase efficiency, allowing faster and more accurate picking, leading to improved overall productivity and cost-effectiveness as well as improving safety in the warehouse, as they can handle heavy or hazardous items, freeing up workers to focus on other tasks;

- In ***Parts-to-Robot*** OPS, gantry robots transport items from the warehouse to a picking station, where a stationary robot picks the required orders (Jaghbeer et al., 2020), similar to *Parts-to-Picker* OPS. However, fully automated picking and picking robots are uncommon and employed only in exceptional circumstances due to their limited capacity for handling irregularly shaped, weighted, and sized items (Vanheusden et al., 2023).

Picker-less Systems

Picker-less OPSs, presented in the central ramification in Figure 2.3, consists of a fully automated warehouse process where no human operator or mobots need to perform the actual picking due to the installation of dispensers and A-frames. Stock items are stored in vertical slots lined up in a distinctive A-shaped frame. A machine automatically takes the bottom item from each slot and puts it into boxes or containers moving along a conveyor belt under the frame. While picking the items from the slots is completely automated, regularly replenishing the hundreds of slots is still physically demanding for human workers (Boywitz et al., 2019).

2.4.2 Performance metrics in OPSs

Performance metrics in OPS refer to a set of key indicators utilized to measure the effectiveness and efficiency of the order-picking process (Staudt et al., 2015). Evaluating these metrics is essential for determining the overall performance of warehouse operations and guaranteeing that customer requirements are fulfilled promptly and cost-effectively (Vanheusden et al., 2023). Some commonly used performance metrics in OPSs include:

- ***Throughput*** - refers to the rate at which orders are processed, usually measured in units per hour.
- ***Lead time*** - is the time elapsed from receiving an order to shipping it to the customer.
- ***Human factors*** - include the comfort and ergonomics of the order picking process for human workers and the health, staff satisfaction and safety implications.
- ***Quality*** - refers to the accuracy of the order-picking process, ensuring that the right items are picked and packed correctly.
- ***Flexibility*** - is the ability of the order-picking system to adapt to changing order patterns and requirements, as well as the ability to handle different types of products and packaging.

- ***Operational efficiency*** - refers to the use of resources such as time, energy, and space, as well as the speed and smoothness of the order-picking process.
- ***Operational costs*** - include the upfront investment in equipment and technology and ongoing operating costs such as maintenance, energy consumption, and labor costs.

Accordingly to Jaghbeer et al. (2020), different OPSs have different performance metrics studied and analyzed. In *parts-to-picker* OPSs, the most commonly researched performance metrics are throughput, lead time, and operational efficiency. Fewer studies analyze human factors, quality, and operational costs. Similarly, in *robot-to-parts* OPSs, there is limited research on the lead time, flexibility, and costs. Research into throughput, lead time, flexibility, and operational efficiency in *parts-to-robot* OPSs is also limited. Although many performance categories have been studied in *picker-less* OPSs, flexibility is the one that has received the least attention. The same article suggests that further research should be directed toward improving the flexibility of *parts-to-picker* systems to be more effective compared with other OPSs, including those using robots.

An in-depth analysis of Boysen et al. (2017) reveals that the authors concluded that grouping orders, known as order batching, can be beneficial as it can lower the number of robots needed. However, it is also important to point out that there is a shortage of real-life data to support this conclusion and that there is a need for more case studies to be conducted to understand the benefits of order batching further.

2.5 Kitting Systems

In mixed-model assembly systems, the role of kitting systems is crucial. Two distinct approaches to kitting have been identified in the literature: traditional kitting and direct kitting (Caputo et al., 2021).

Traditional kitting involves the manual or automatic selection, sorting, and organization of components into kits within a warehouse setting. This approach is widely used in industry. In contrast, *direct kitting* utilizes digital manufacturing techniques such as additive manufacturing to fabricate and assemble customized kits simultaneously (Hanson and Brolin, 2013). The potential for reduced handling and increased efficiency through this approach is hindered by the current limitations of additive manufacturing technologies and their limited adoption in the industry, as stated in Khajavi et al. (2014).

This dissertation is focused on traditional kitting, where pre-manufactured parts are assembled into kits as a separate process from the actual manufacturing. The different forms of kitting systems are described and distinguished by the degree of automation in the distinct stages of picking and kitting the components.

Drawing from a literature review and insightful expert interviews within the industry, Hanson and Medbo (2016) undertook an analysis encompassing 15 instances within the automotive sector. Their study focused on discerning critical design and contextual facets inherent to kitting systems, which wield significant influence over person-hours consumption. The outcomes of their investigation underscore the preeminent design factors that exert the most pronounced impact on kitting efficiency, specifically the mean duration required for picking each component and the spatial density of picking. These factors include the nature and dimensions of storage bins, the configuration and structural composition of storage racks, the magnitude of batch processing, and the spatial extent of the picking region. Remarkably, the size of the components, considered an input parameter, engenders indirect implications on kitting efficiency by its influence on all the aforementioned performance metrics (Subsection 2.4.2).

According to Caputo et al. (2021), the kitting process can be divided into different stages, such as retrieving parts from storage, selecting and picking the appropriate number of parts for the kit, and assembling the kit. The assembly process encompasses more than just placing the parts in the kit container. It could also include activities like counting or weighing the parts to confirm their correct quantity, preparing the components before their inclusion in the kit (e.g., cutting to size, removing the packaging, and conducting quality control), arranging the parts in the correct order and location within the kit, and keeping track of any missing components that need to be added later.

In this way, the picking process generally involves two distinct stages: retrieving the necessary parts and picking parts into a kit. The distinction between these two steps only becomes relevant when different methods or resources are used to perform each stage. So, in simpler terms, the kitting process includes one step of picking the required components and another step of kitting these components into the final kit.

Different kitting systems are discussed and presented below, where they were classified into different types to facilitate referring to them during the report. Understanding the different types of kitting systems, their characteristics, and their strong points can help differentiate in order to choose and refine the best approach for improved efficiency.

2.5.1 Type A - Manual Picking and Kitting

In this case, Type A, considering manual picking and kitting, involves human operators physically selecting the necessary components for a specific kit from storage containers in the warehouse (see Figure 2.4). These operators may use a paper-based pick list, which provides information on the specific components required for each kit, or a picking-by-light system to assist in identifying the correct components. Once the components have been selected and verified, the operator will place them in kit boxes in an AGV for transport to the designated location on the mixed assembly line.

It is important to mention that the manual kitting process may also be supported by other equipment such as a barcode scanner, RFID reader, pick-by-light, pick-by-voice, pick-by-HUD or picking carts for the operator to transport the parts

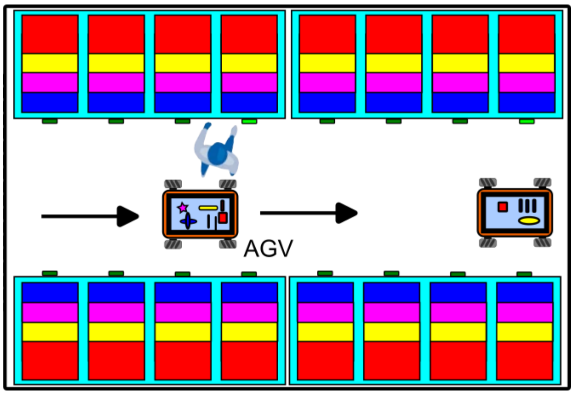


Figure 2.4: Schematic representation of the Type A kitting system: picking and kitting performed by a human operator, using a pick-by-light system.

(Fager et al., 2019b). These tools can help improve the efficiency and accuracy of the kitting process.

This kitting system has some disadvantages, such as the cost of manual labor, the risk of ergonomic issues, and the potential for quality problems (Fager et al., 2020a). Despite these drawbacks, manual kitting remains a popular choice as a prevalent method for kit preparation in the industry due to its versatility and ability to adapt to different circumstances.

2.5.2 Type B - Automated Picking and Kitting

A fully automated picking and kitting system, designated as Type B, involves advanced automation technologies to perform the entire kit preparation process without human intervention (see Figure 2.5). These systems typically include a combination of robots, conveyors, and other automated equipment that work together to pick, sort, and place components in kit boxes (Sellers and Nof, 1989). Automation technology in these systems can range from simple pick-and-place robots to more advanced systems that use machine learning and computer vision to identify and manipulate components precisely (Rieder et al., 2021).

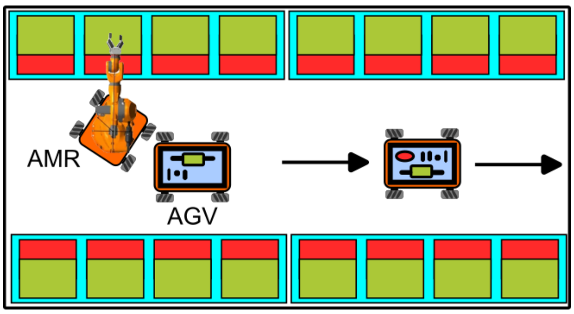


Figure 2.5: A representation of the Type B kitting system, showcasing the integration of an AMR for picking and AGV for transporting kits to the assembly line.

One key advantage of fully automated picking and kitting systems is the ability to operate at a much higher efficiency and speed than traditional manual or semi-automated systems. This is due to the high precision of the automated equipment and repeatability in the process, which allows for more efficient and accurate component handling (Jaghbeer et al., 2020). In addition, these systems can also help reduce labor costs since they do not require human operators to perform the kit preparation process.

Furthermore, these systems can improve quality, as automated systems are less prone to human errors. They can also be programmed to perform several quality checks throughout the kitting process, such as checking for missing or incorrect parts, and provide real-time feedback to operators (Azadeh et al., 2019).

However, fully automated kitting systems are typically more expensive in terms of maintenance than traditional manual systems and may require specialized expertise to operate and maintain. In addition, implementing these systems may require significant changes in the logistics and infrastructure of the organization, which can be a major challenge for some organizations (Sgarbossa et al., 2020).

Implementing the Type B solution must be thoroughly evaluated in terms of performance and cost, as deploying such a system involves a highly significant financial investment that must be justified by substantial benefits (Caputo et al., 2021).

2.5.3 Type C - Human-Robot Collaborative Picking and Kitting

The Type C kitting system, referred to as the Human-Robot Collaborative Picking and Kitting System, is a hybrid solution that utilizes a blend of manual and automated techniques for the picking and kitting components. This system involves dividing the same picking area of the warehouse into two sections, one for manual picking, performed by human operators, and the other for automated picking, performed by AMRs, also known as mobots (see Figure 2.6). The human operator and the AMR work concurrently, each responsible for selecting the components from their designated section and placing them in kit boxes on an AGV for transportation to the assembly line.

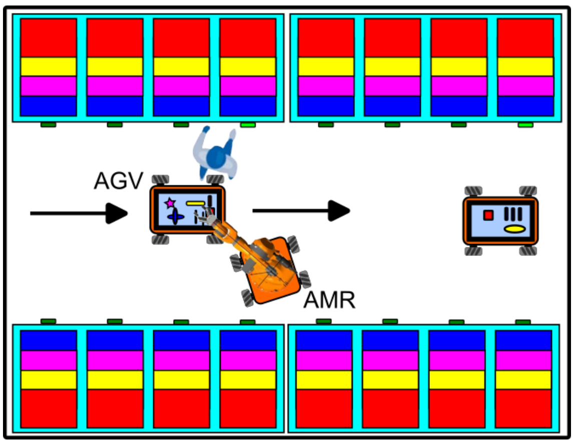


Figure 2.6: Schematic representation of the Type C hybrid kitting system, where human operators and AMRs work in parallel to pick and kit components for the mixed-model assembly line.

This approach addresses some of the limitations of the fully automated Type B kitting system (Subsection 2.5.2) by allowing the use of AMRs to pick components with similar and uniform sizes, weights, and geometries, reducing the need for specialized grippers and minimizing performance issues (Coelho et al., 2018). Additionally, limiting the movement of the AMR to a single aisle reduces the distance it needs to travel, increasing its efficiency.

However, it should be noted that this solution still presents certain challenges. When coordinating the actions of the AMR and the human operator, achieving a synchronous process can be difficult (Fager et al., 2020b), and it may not handle all components required by the assembly line. Furthermore, the operation time of the AMR may be impacted by the need to place the selected components in the correct location in the AGV kit box.

2.5.4 Type D - Hybrid Robotised/Manual Picking and Kitting

The solutions presented in previous sections, Types B and C (subsections 2.5.2 and 2.5.3, respectively), can pose a challenge in terms of performance resulting in a picking and kitting cycle time that is not compatible with the required pace of the assembly line (Caputo et al., 2021). Several factors significantly impact the duration of the picking and kitting task by the AMRs, including:

- AMR's time between two consecutive picking positions;
- AMR's time to pick components;
- AMR's time to place the component in the correct location in the kit box;

The Type D kitting system addresses these problems by dividing the picking zone into two areas, with one area designated for manual picking, performed by human operators, and the other area designated for automated picking, performed by AMRs (see Figure 2.7). In the first area, the AMR is responsible for picking components and bringing them to a buffer, which eliminates the need for the AMR to place the component in the correct position in the kit box, being a task developed by the human operator. This approach is similar to the Type B solution, but the AMR is only responsible for the picking operation, not the kitting directly. This reduces the time required for the mobot to complete its operations and improves its performance (Boudella et al., 2018).

In the second zone, the operator prepares the kit boxes, picks the components prepared by the AMR, and places them into the kit box in the tugger train. Once the operator finishes these tasks, it collects all the remaining parts. This way, the Type D solution allows for a more efficient workflow by separating the picking and kitting functions between the human operators and the AMRs, reducing the time required for the AMR and increasing its performance.

The human operators and the AMR work simultaneously and independently, allowing an asynchronous harmonized operation, each one responsible for picking

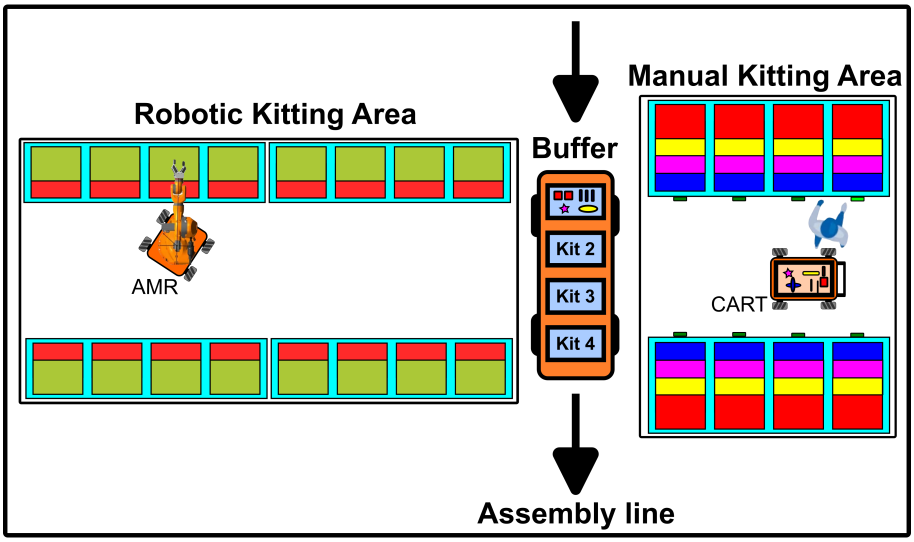


Figure 2.7: Representation of the Hybrid Robotised/manual picking and kitting (Type D) showing the division of the picking zone into two sections.

components from their designated aisle and placing them in kit boxes on an AGV for transportation to the assembly line. This allows for smooth and efficient coordination between the two agents, reducing the risk of errors and increasing the overall performance of the kitting process.

2.6 Kitting optimization and costing models

Robotics and other advanced technologies can be used to automate the kitting process. By integrating automated systems, productivity, efficiency, and accuracy can be improved significantly, but, as mentioned by Caputo et al. (2021), the use of fully robotic kitting systems is limited because of the technical difficulties that robots face in completing tasks like selecting individual parts from bulk containers, placing parts in kit containers in the correct orientation, removing the packaging, and inserting cardboard sheets and dividers into parts containers. Although some experiments have been conducted with such systems, they are not widely used due to these challenges.

In addition to technical difficulties, implementing (hybrid) robotic kitting systems is also hindered by economic considerations. To understand the economic viability of such systems, it is essential to develop and analyze cost models. These models consider factors such as capital costs, operating costs such as the costs related to energy consumption, maintenance costs, and the costs associated with downtime or failure. When analyzing these costs with the different models, it is possible to determine the overall economic feasibility of a fully robotic kitting system and compare it with other alternative solutions. In this way, the role of cost models in guiding the implementation of automated kitting systems is significant (Boysen et al., 2015).

Caputo et al. (2021) examines the cost-effectiveness of different kitting systems.

The study first creates a categorization framework for different kitting systems and then develops a comprehensive planning and cost model to compare the costs of manual and automated kitting systems. It is considered four types of kitting systems: Automated Retrieval – Manual picking and kitting (with AS/RS) and a buffer conveyor, where operators proceed with picking and kitting); Manual Picking – Manual kitting (traditional warehouse with operators that perform picking and kitting using a paper pick list); Automation-assisted Picking – Manual kitting (similar to the previous system, but pick-to-light system is incorporated) and a Hybrid Robotised/manual picking and kitting (consisting of a zone with a totally automatic kitting system complemented by a totally human operator kitting system to pick and kit the missing parts). The developed model evaluates the equivalent annual cost of several factors, such as investment in equipment (AS/RS and cranes), labor costs, energy consumption, warehouse and storage area space, and costs associated with correcting errors for the kitting systems considered, as well as the determination of resources specific for each type. In this work, the required throughput rate and the daily gross volume are determined for all parts needed to meet the daily demand to achieve the average cycle time of the process. For the last kitting system proposed, the authors determine the number of robots (N_A) using an iterative procedure, as well as the length of each aisle L, because the time robots take to complete a kit depends on the length of the aisle. The findings of the study indicated that automated retrieval systems are economically advantageous in most cases, except when demand is low or labor costs are minimal. The model also showed that systems designed to avoid errors are only cost-effective if the cost of a single error is substantial.

In "AMR-assisted order picking problem (AOPP)", Žulj et al. (2022) highlights a real-world challenge faced by a German automotive Original Equipment Manufacturer (OEM) in its warehouse, where over half a million test components are stored and numerous customer orders are received. To streamline the order-picking process, customer orders are grouped and transported by a fleet of AMRs. The warehouse is divided into separate zones, each comprising a single picking aisle, and an order picker collects the items of a customer's order stored in their zone and passes them to the AMR. The authors propose a mixed integer programming (MIP) approach for the AOPP and show that it is an NP-hard problem. To tackle this, they present a two-stage heuristic solution that consists of an Adaptive Large Neighborhood Search (ALNS) component for batching customer orders. The authors conduct experiments to evaluate the impact of different algorithmic features on solution quality and demonstrate that their approach can quickly find high-quality solutions for smaller instances. Additionally, they explore the effect of increasing the AMR fleet size and changing the travel and walking speed ratios between AMRs and order pickers to minimize total customer order tardiness. The results reveal that increasing the speed ratio or the fleet size can significantly reduce total delay, providing valuable insight into the problem. This article is relevant to this dissertation on optimizing robotic kitting systems.

The study by Fager et al. (2019a) explores the benefits of using collaborative robots, or *cobots*, in the kit preparation and order batching processes in mixed-model assembly operations. The authors aim to determine the improvement in efficiency that can be achieved by utilizing *cobots* in these tasks. They use a modeling approach and conduct laboratory experiments to compare the cycle time between two scenarios: manual picking and sorting tasks and cobot-assisted kit preparation and order batching. The authors calculate the order picking time for each scenario. For the manual scenario, the total order picking time consists of picking, sorting, and travel times. For the cobot scenario, the total order picking time includes the picking and travel time (determined in a similar way to the manual scenario) and the collaborative time, representing the time for the operator to place the Stock Keeping Units (SKUs) in the collaborative zone for the robot to pick and sort the components, with the time for the first component being more significant than the subsequent ones. The findings of the study indicate that using *cobots* for sorting tasks leads to similar average cycle times compared to manual operations, with reduced fluctuations in the cycle time. Although the model is a basic representation of a real-world industrial setting, further research is required before making any actual implementations. The significance of the paper is in the modeled application of cobot-assisted kit preparation, which can be a valuable tool for evaluating the feasibility of incorporating *cobots* into their systems. With this model, authors suggest exploring the influence of *cobots* on other aspects of kit preparation and the effect of different variables.

In Fager et al. (2021b), the cost difference between a manual and a cobot-supported process is also evaluated, taking into account the costs with operators, equipment and quality, finding that a cobot sorting is more robust when high yearly order volumes exist and when orders have more frequently common components.

The authors of Boudella et al. (2018) introduce a mathematical model aimed at improving the allocation of different components (SKUs) between a robot and a human operator during the preparation of a series of kits, using a Mixed Integer Programming (MIP) model. It contributes to research, developing and modeling some critical processes in the cycle times for both Robotic and Manual Kitting. The model was tested using data from an automotive company, and the results demonstrate that certain requirements must be satisfied in terms of component features and available floor space to make the automation of the kitting process feasible. Although the model presents an initial approach to optimizing the hybrid robot-human kitting system, further and better research is necessary by refining the model to account for unpredictable demand and testing it in different settings to increase its robustness. Additionally, the model can be modified to accommodate different configurations, such as using two robots, and can serve as a foundation for evaluating manual kitting systems. However, the model has certain limitations, such as the assumption of parts being stored solely in small containers and not considering pick-to-light or voice-based manual kitting systems.

The authors in Schmid et al. (2021) have created a MIP model to design kitting cells with a U-shaped configuration and applied it to real-world data from the automotive industry, conducting a study on improving the design of the cells. The model aims to minimize the total cost, which includes the expenses for restocking, walking, investment, and space. The findings show that this model enhances the efficiency of the kitting process compared to conventional and heuristic approaches. However, the study was centered on manual kitting and a relatively small number of part families and variants.

Total costs and throughput are evaluated in a collaborative workspace for order picking operations by Winkelhaus et al. (2022), presenting a simulation model considering several parameters of hybrid kitting systems, and it shows that it is generally more efficient than fully manual or fully robotic order picking systems.

Several articles focus on comparing and choosing different line-feeding modes. Gaub (2016) developed a MIP model to decide the appropriate line feeding method for each component, between line stocking, kitting, and sequencing modes, being the model applied to data from a supplier in the automotive industry, for a mixed-model assembly line. In Caputo et al. (2015a), an integer linear programming mathematical model was designed to allow choosing between kitting, line stocking and just-in-time delivery policies through economic comparison, but it is developed in this case for single-model assembly lines operating in a deterministic environment. For evaluating the parts assignment between kitting and line stocking, Limère et al. (2012) also developed a mathematical cost model considering a case study from a Belgium automotive company, showing that in cases of space constrain, kitting all parts isn't the most cost-effective strategy.

To address the planning and scheduling of multistage assembly lines, Vieira et al. (2022) presents a Recursive Optimisation-Simulation Approach (ROSA) methodology with an iterative process to optimize production planning, combining a two-tier Mixed-Integer Linear Programming (MILP) model with a detailed discrete event simulation model. This method yielded near-optimal solutions encompassing essential determinants like lot-sizing choices, production order release schedules, task delegation between human workers and robots, and the optimal robot deployment for each period.

Accounting for fully robotic systems, Boudella et al. (2016) modeled kitting operations in a case with a robot arm mounted on a rail system that travels along a narrow aisle to pick parts and proposed a method to reevaluate performance in terms of cycle times. In literature, research is mainly focused on robotic-picking performance evaluation to understand its feasibility in a real-world scenario (Krueger et al., 2019).

2.7 Energetic Efficiency of AGVs

The literature related to power energy consumption aspects of Automated Guided Vehicles (AGVs) was explored through several noteworthy articles. Meißner and Massalski (2020) conducted an in-depth investigation to model the electrical power and energy consumption of AGVs using several movement modules to analyze the translatory, the rotary, the lifting and lowering movements of the load-carrying platform, as well as assessing the impact of varying speeds on overall energy consumption.

Li et al. (2020) investigated the influence of decentralized storage policy on order picking performance efficiency, emphasizing the importance of the methods in reducing AGV energy consumption. Moreover, the work of Javied et al. (2018) explored and developed an energy monitoring and management system in an Industry 4.0 context to enhance the ecological footprint and maintain operational efficacy. Collectively, these studies contribute to the evolving discourse on improving energy efficiency of AGVs, underscoring the significance of sustainable energy practices in industrial automation.

Kara et al. (2007) focused on the heterogeneous AGV routing problem considering the minimization of the energy consumption with relationship to loading weight, demonstrating ways this energy consumption can be decreased through a particle swarm optimization (PSO) algorithm provided. Kara et al. (2007) considered the routing problem with the energy consumption due to weight and distance traveled. On the other hand.

In the work developed by Zhou and He (2021), it is presented a mathematical model that aims to minimize the total energy consumption and the total line-side inventory in a static semi-kitting strategy for mixed-flow assembly lines.

2.8 Critical Analysis

A review of the literature has shown that several studies have been conducted on kitting and picking processes in the automotive industry, with an adequate modeling base as demonstrated by works such as Caputo et al. (2021) and Boudella et al. (2018). However, while these studies have provided a solid foundation, there is still space for improvement and further research in this field, such as the limitations regarding automation configurations and weight and size of the parts.

To enhance the current state of the art in this area, the following improvements could be made:

- Extending and developing models for additional automation configuration designs.
- Testing the models more comprehensively to understand better the impact of different factors such as the weight and size of parts, number of AMRs available, and picking errors.
- Conduct and develop models to explore the fraction of parts that can be automatically kitted and picked or need to be kept in a manual operation.

The Type D kitting system stands out when compared to other kitting systems, such as Type A, B and C, because it addresses many of the challenges faced in modern manufacturing environments. The Type D system is designed to handle heterogeneous and irregular components, becoming more common in the automotive industry as manufacturers strive to create new and innovative products. This system is also more flexible than other kitting systems, allowing for more straightforward adaptation to new or changing requirements compared to Type B. The Type D system uses a combination of automation and manual labor, which allows for a higher level of control and precision in the kitting process than the Type C system. This results in more efficient and accurate kitting, reducing the risk of errors and increasing the overall productivity of the manufacturing process compared to the Type A kitting system. In conclusion, the Type D kitting system has the potential to be more effective in modern manufacturing environments due to its flexibility, control, and ability to handle heterogeneous and irregular components.

This dissertation will explore the potential benefits and challenges of layout designs inspired by the Type D kitting system (subsection 2.5.4) and investigate how it can be implemented in a model that can truly describe it. Solving methods such as mathematical programming models or heuristic approaches should be explored to compare to manual and collaborative kitting systems. A detailed analysis aims to demonstrate the potential of this system to improve the kitting process in modern manufacturing environments in the automotive industry, particularly when facing heterogeneous and irregular components.

In kitting operations, the cycle time and its cost are crucial factors that need to be optimized, as demonstrated by the effect that errors can have on these metrics. It is also essential to ensure coordination and synchronization in the kitting process.

Additionally, the proposed kitting system should be tested with adequate data to see if it can be successfully implemented in manufacturing settings of the automotive industry. This will support and validate the results and provide a more accurate understanding of an efficient kitting system. The reviewed research provided valuable insights into the kitting and picking processes and contributions to the ongoing efforts in this field.

The impact of the kitting process on the energy efficiency of AGVs remains an underexplored area of research. A comprehensive research will be undertaken into a complete robotic kitting solution with the aim of identifying effective strategies for minimizing energy consumption by AGVs. This study will aim to be a promising addition to the ongoing efforts of different industries to automate warehousing and optimize processes, and it can drive progress in robotic kitting technologies, improving efficiency and competitiveness in the automotive sector.

Chapter 3

Methodology

The methodology chapter describes the approach to developing hybrid kitting systems and the operational research model for optimizing kitting operations. This chapter begins with the comprehensive layouts of the hybrid kitting systems, highlighting the various components involved and their specific roles. The chapter then proceeds to describe the processes related to kitting operations considered during the development of the models, providing a clear understanding of how the systems operate. Furthermore, the chapter discusses the SKU assignment model developed and its related constraints, demonstrating how it was formulated to optimize the kitting process. Overall, this chapter thoroughly explains the methodology employed in this study, allowing the reader to understand better the research methodology and the framework used to analyze the data.

3.1 Hybrid kitting systems description

After analyzing the State of the Art (Chapter 2) with the leading research developments and the challenges faced by the industry to implement an efficient kitting system, two innovative layouts are presented: the Asynchronous Hybrid Kitting (AHK) System and the Sequential Hybrid Kitting (SHK) System.

3.1.1 Asynchronous Hybrid Kitting (AHK) System

The Hybrid kitting system described in this subsection, designated by AHK System follows a starting point based on the layout developed by Boudella et al. (2018), which has been improved on its characteristics and kitting organization, namely how components are transported to the kitting zone. The process involves two semi-independent areas: a robotic kitting area with an Autonomous Mobile Robot (AMR) picking and placing parts onto an Automated Guided Vehicle (AGV) box, which moves later on to the sorting and kitting area, where the kits are prepared, and a collaborative kitting area, where a human operator completes the kits with the support of a pick-to-light system and AGVs to transport the parts. The tugger trains act as a buffer between the two areas, allowing for a balanced distribution of parts and improved productivity.

Figure 3.1 shows a set of kits being prepared, composed of components for each End Product (EP) to the assembly line, in this kitting system. In the automotive industry, each part/component used in a EP can have different variants represented by different and unique Stock Keeping Units (SKUs), differing in terms of one or several aspects related to its characteristics. This SKUs can be packaged with interlayers, dividers, styrofoam boxes, plastic bags, or others to ensure quality to SKUs, preventing possible damage.

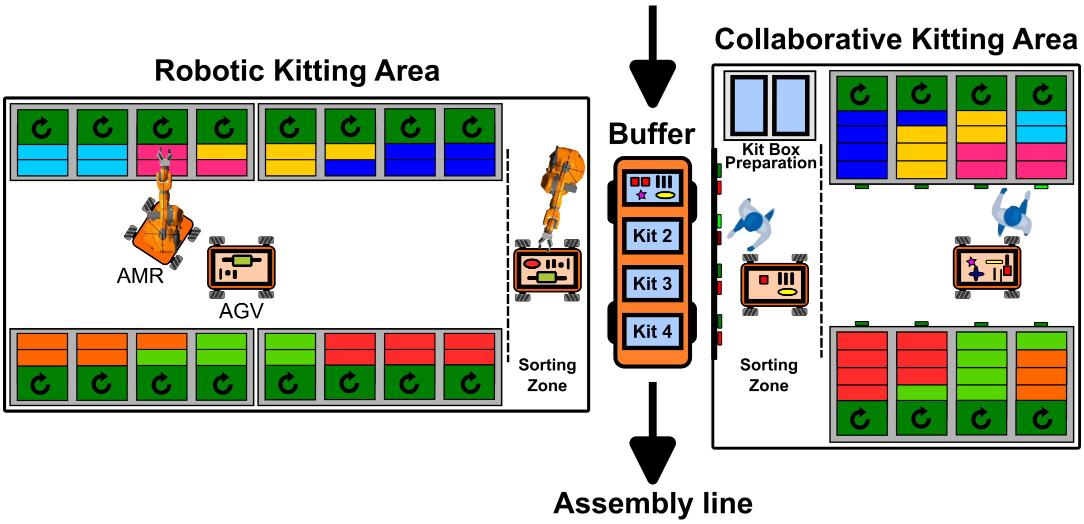


Figure 3.1: Representation of the AHK System.

As can also be seen in the figure, there are racks in the storage area where the components are stored in bins with different sizes and are made of different materials, some of which can be foldable. The colors in the racks represent bin storage locations of the same SKUs or different SKUs being variants for a specific category.

To build an EP, the parts are placed in kitting boxes, where each box is formed so that all the components needed at a point of use on the assembly line can be placed in one or more boxes grouped into a kit. In the automotive manufacturing industry, a basic EP consumes basic components while a more configured EP uses a broad spectrum of components.

In the first step of this kitting process of the robotic kitting area, a AMR needs to move from its previous location to the correct storage location, where the component to be picked is located. In a second step, the AMR picks the components and places them on a box fixed to a AGV that needs to be available near it, which will be filled accordingly to the Bill of Materialss (BOMs) accepted. The AGV box receives the pieces for the later mounted kits, allowing a faster picking process and considering an adequate strategy to store parts in the warehouse according to their class, weight, and fragility.

In addition to picking the parts, the AMR is responsible for removing the empty bins in the storage racks of the robotic kitting area to the evacuation ramps, located on the third level of the racks, according to the Figure 3.1, represented by the dark green color, and removing the dividers and interlayers from the parts, implying the necessity of gripper adaptation to accommodate the size, shape, and material constitution.

When the AGV box is full, a third step begins, where the AGV travels from its position (near the AMR) to the sorting and kitting area. While this happens, a new AGV should be moving to a close radius of the AMR to continue the picking process. After the AGV reaches its designated location in the sorting zone, the fourth step begins, where a fixed manipulator is installed that starts identifying the parts, followed by picking and sorting them to the correct kit on the tugger train (fifth step), which will take the kit to the final position on the assembly line, which is available with the destination kit boxes already placed to be loaded with the different parts.

The kits being mounted in the tugger train are completed with the specific parts that cannot be picked by manipulators, components in packages with plastic bags or foam protection, or that were allocated to the manual collaborative kitting side due to optimization and system balancing purposes. An analogous set of steps occurs in this area with the difference related to the substitution of the AMR by a human operator that proceeds with the identification of the parts with the support of the BOM and a pick-to-light system to reduce the time needed for searching components, picking them to the AGV that will follow the operator along the storage racks. Additionally, the operator(s) proceeding with the picking will also remove all the packaging of components into a disposal container.

The collaborative kitting area stores parts using a volume-based approach, meaning frequently requested components are located near the output point to minimize the distance traveled by the operator.

In the sorting and kitting zone of the collaborative kitting area, no manipulator but a human operator is picking the parts from the AGV to complete the correct kits prepared by the robotic kitting area. To reduce errors in the sorting process by the human operator, it should be supported by a kit-to-light system (similar to a pick-to-light system) to help place the part in the correct kit box. This operator will also be responsible for correctly positioning the kit boxes in the tugger train to receive the components from both the robotic and collaborative kitting areas.

In this proposed system, the tugger trains act as a buffer that is assumed to be large enough to decouple the activities presented on both sides (robotic and collaborative kitting areas) and operate in a certain semi-independent way, i.e., while the operator is completing the kits, the robotic side is proceeding with the BOM to the following kits. When all the kits are assembled, the tugger train will leave the kitting zone to deliver the kits to the Border of Line (BoL).

To achieve an efficient kit production line, the fraction of parts to be distributed through the robotic or collaborative kitting area must be well balanced, achieving a similar working time for both sides of the system, improving productivity, and avoiding idleness.

3.1.2 Sequential Hybrid Kitting (SHK) System

The SHK System introduces a slightly distinct layout concept from the previous model, adopting an assembly line approach to kit formation. This system optimizes the kit production process by incorporating key modifications that enhance efficiency and reduce handling steps.

In this system (Figure 3.2), the AGVs are equipped with the kitting boxes required for the assembly line, eliminating the need for subsequent sorting operations, which are positioned alongside the pickers to facilitate the completion of multiple kits. An operator initially prepares the kit boxes on the AGVs, ensuring their readiness to receive components.

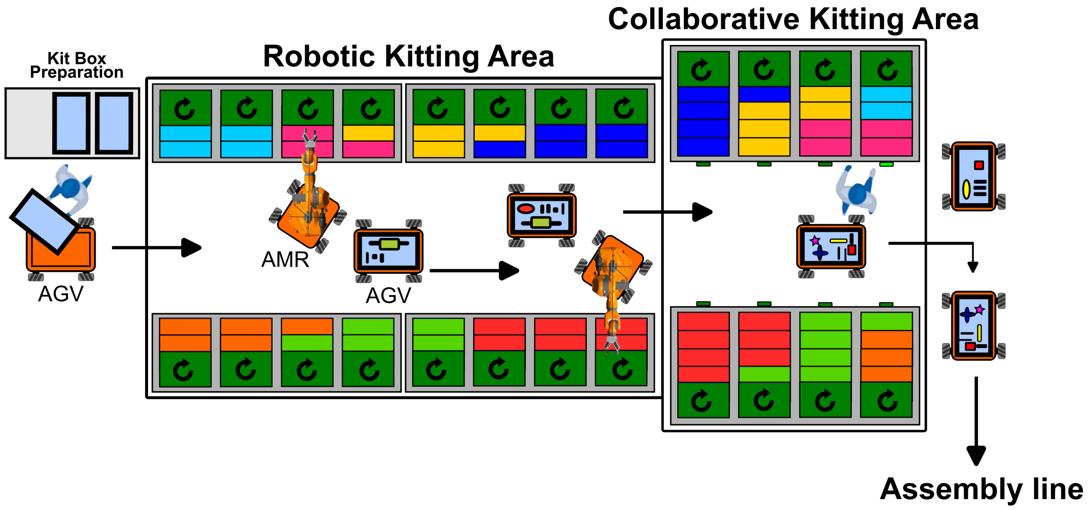


Figure 3.2: Representation of the SHK System.

The AGVs follow a unidirectional path, akin to an assembly line, beginning in the robotic kitting area. Here, an AMR carries out the picking of components and places them onto the AGV. The AMR executes the picking process, removes any interlayers and dividers in the components bins, and relocates empty containers into the evacuation ramps. This step ensures that the components are optimally placed for efficient kitting.

After collecting all the necessary components in the robotic kitting area, the AGV transitions to the collaborative kitting area. In this zone, a human operator takes over picking components to complete the kits. The operator is supported by a bill of materials (BOM) and a pick-to-light system streamlining the retrieval process. The operator also meticulously removes all packaging materials surrounding the components.

The AGVs then assemble into a logistics train configuration, ready to proceed to the assembly line, similar to the tugger train in the previous layout. This sequential hybrid approach aims to balance the workload between the robotic and collaborative kitting areas, ensuring optimal working times for both sides of the system. Ultimately, the SHK System maximizes efficiency by integrating the advantages of robotic precision and human skill, paving the way for a more streamlined and productive assembly process.

3.2 Modeling

The models developed are based on the model proposed by Boudella et al. (2018), which have been adapted and improved to correctly represent the characteristics of the innovative layout and organization of the kitting presented.

The aim of the Mixed Integer Programming (MIP) models proposed is to determine the best (optimal) way to distribute SKUs between the robotic area and the collaborative area to maximize the efficiency of a kitting system. To do this, we evaluate the time to complete the necessary operations during a typical preparation cycle and over a period representing the demand for different EPs. Each product requires a specific list of SKUs with the number of parts needed. This information is used to obtain the frequency at which each SKU is used and the average number of components required based on the number of EPs produced during the reference period.

After finding the optimal assignment, it is essential to ensure that the resulting throughput is equal to or greater than the throughput of the assembly line. In other words, if the throughput of the hybrid kitting system is higher than the throughput of the assembly line, it can be considered a possible and practical replacement for the manual kitting system. If not, then the design and layout of the kitting system should be improved. Once this is done, the workload between both sides of the system should be allocated in the warehouse.

Firstly, the indexes and parameters will be presented, followed by the decision variables and the objective function for the AHK System and after for the SHK System.

3.2.1 MIP model for the Asynchronous Hybrid Kitting (AHK) System

Indexes

The indexes outline the data entities within the proposed Mixed Integer Programming (MIP) models.

- "R" - indicates that a certain parameter or variable refers to the area of robotic kitting;
- "C" - indicates that a certain parameter or variable refers to the area of collaborative kitting;
- $i = [1, 2, ..., Z]$ - unique identifier of SKUs within the kitting process (where Z is the total number of SKUs).

Parameters

The parameters of the model represent information sourced from input data or realistic estimates and may need to be updated as conditions change. They should be defined accurately and reflect the characteristics of the kitting problem being modeled because they can significantly impact the results of the model, so it is important to use the best available information when defining them.

General Parameters

- BS - Batch size, representing the number of EPs prepared simultaneously in the cycle time of the kitting preparation process;
- Z - Total number of SKUs in the kitting area;
- A - Total area available for the hybrid kitting system (m^2);

Components and Bins Parameters

- n_i - Number of components needed in the BOM of SKU i;
- f_i - Frequency of usage of SKU i in the EPs;
- BW_i - Storage bin width of SKU i (m);
- P_i - Number of components of SKU i in a complete storage bin;
- IL_i - Number of interlayer sheets in a complete bin of SKU i;
- D_i - Number of dividers in a complete bin of SKU i;
- Fo_i - Number of foam protections in a complete bin of SKU i;
- PB_i - Number of plastic bags in a complete bin of SKU i;
- Vol_i - Volume of SKU i (m^3);
- M_i - Weight of SKU i (kg);
- $feas_i$ - Feasibility of SKU i for robotic picking;

Robotic Kitting Parameters

- Bg - Percentage of t_{image} that occur in background;
- AW^R - Aisle's width in the robotic kitting area (m);
- RD^R - Storage Rack's depth in the robotic kitting area (m);
- S^R - Horizontal spacing between two successive bins (m);

- RL^R - Standard rack Length in the robotic kitting area (m);
- N^R_{levels} - Number of levels in the storage racks in the robotic kitting area;
- F^R - Number of facades in the robotic kitting area;
- Ps^R - Picking sides in the robotic kitting area;
- AMR - Number of AMRs working in the robotic kitting area;
- v_{AMR} - AMRs average velocity (m/s);
- v_{AGV} - AGVs average velocity (m/s);
- $Sort^R$ - Distance in the sorting zone traveled by the AGV (m);
- t^R_i - Time for the AMR/fixed manipulator to pick SKU i (s);
- t_{image} - Average time for the AMR/fixed manipulator controller to capture and process a single image of a bin(s);
- t^R_{bin} - Average time for the AMR to pick an empty bin and dispose it in the evacuation zone (s);
- t^R_s - Average time for the fixed manipulator to pick a part from the AGV to the kit box (s);
- t^R_{IL} - Average time for the AMR to remove an interlayer sheet from a bin (s);
- t^R_D - Average time for the AMR to remove a divider from a bin (s);
- $t_{gripper\_parts}$ - Average time for the AMR to change the gripper to pick different parts (s);
- $t_{gripper\_pack}$ - Average time for the AMR to change the gripper to pick packaging items (s);
- $t_{gripper\_bin}$ - Average time for the AMR to change the gripper to pick empty bins (s);
- Cal - Additional proportion of time needed for gripper calibration;
- PE_i - Probability of occurring a picking error during the initial attempt of picking SKU i;
- PE_{bin} - Probability of occurring a picking error of empty bins;
- PE_{sort} - Probability of occurring a picking error sorting parts
- $PE_{interlayer}$ - Probability of occurring a picking error of interlayer sheets;
- $PE_{divider}$ - Probability of occurring a picking error of bin dividers;
- Col - Impact on collaborating with a human operator on completing kits;

- AR_{parts} - Parameter describing an efficient assignment rule for changing the gripper to pick a different part;
- AR_{pack} - Parameter describing an efficient assignment rule for changing the gripper to pick a different packaging item;
- AR_{bins} - Parameter describing an efficient assignment rule for changing the gripper to pick a bin;

Collaborative Kitting Parameters

- Ef_{kit_prep} - Parameter describing the efficiency in preparing kit boxes;
- AW^C - Aisle's width in the collaborative kitting area (m);
- RD^C - Storage Rack's depth in the collaborative kitting area (m);
- S^C - Horizontal spacing between two successive bins (m);
- RL^C - Standard rack Length in the collaborative kitting area (m);
- N^C_{levels} - Number of levels in the storage racks in the collaborative kitting area;
- F^C - Number of facades in the Collaborative kitting area;
- Ps^C - Picking sides in the collaborative kitting area;
- OP - Number of operators working in the collaborative kitting area;
- $\bar{v}_{OP}$ - Human operators average velocity (m/s);
- $\bar{v}_{AGV}$ - AGVs average velocity (m/s);
- $Sort^C$ - Distance in the sorting zone traveled by the AGV (m);
- sim_i - Number components of SKU i that a human operator can pick simultaneously;
- sim_{pack} - Number of packaging items that an operator can pick simultaneously;
- t_{kp} - Average time for the operator to prepare a single kit box (s);
- t_{p2l} - Average time required for the pick-to-light system to send data packages to the modules (s);
- t_{obs} - Average time required for the operator to locate and identify a single pick-to-light module turned on (s);
- t^C_i - Time for the operator to pick SKU i (s);
- t^C_{bin} - Average time for the operator to pick an empty bin and dispose of it in the evacuation zone (s);

- t_s^C - Average time for the operator to pick a part from the AGV to the kit box (s);
- t_{IL}^C - Average time for the operator to remove an interlayer sheet from a bin (s);
- t_D^C - Average time for the operator to remove a divider from a bin (s);
- t_F - Average time for the operator to remove a foam protection from a bin (s);
- t_{PB} - Average time for the operator to remove a plastic bag from a bin (s);
- EC_{com} - Error correction factor related to additional data packages resent;
- EC_{obs} - Error correction factor related to operator failing to observe a turned-on module;
- EC_{detect} - Error correction factor related to pick-to-light module proximity sensor failure, leading to the module's light being turned off incorrectly;
- EC_{sort} - Error correction factor related to the operator rectifying any mistakes by picking a wrongly placed part from one kit box and relocating it to the correct kit box;

Tugger Train Parameters

- $TUGGER$ - Total number of tugger trains available;
- T_{run} - Tugger train's displacement time (s);
- t_{stop} - Tugger train's single stopping time (s);
- N_{kits_MAX} - Tugger train kit capacity (s);

Technical Parameters

- M_{AGV} - Maximum weight capacity of the AGV (kg);
- Vol_{AGV} - Maximum volume capacity of the AGV (m^3);
- M_{kit} - Maximum weight capacity of the kit box (kg);
- Vol_{kit} - Maximum volume capacity of the kit box (m^3);

Decision Variables

The decision variables correspond to the unknowns of the problem that the model aims to determine, subject to constraints, and the information they represent enables to provide a clear answer to the original challenge, supporting the decision-making process related to attributing SKUs to the robotic kitting area or the collaborative kitting area, which is represented by:

Main Decision Variables

- Binary decision variables representing the allocation of SKUs to the robotic or collaborative kitting areas;

$$x_i = \begin{cases} 1, & \text{if SKU } i \text{ is assigned to the robotic kitting} \\ 0, & \text{otherwise} \end{cases} \quad \forall i = 1 \dots Z \quad (3.1)$$

Auxiliary Decision Variables

- N_{kits} - Integer decision variable representing the number of kits needed to be mounted;
- $N^R_{AGV\_trips}$ - Integer decision variable representing the number of AGV trips performed in the robotic kitting area;
- $N^C_{AGV\_trips}$ - Integer decision variable representing the number of AGV trips performed in the collaborative kitting area;
- $N_{tugger\_train\_trips}$ - Integer decision variable representing the number of tugger train trips performed;
- a - Continuous decision variable representing the maximum cycle time, used due to the linearization;
- $b_i, \quad \forall i = 1 \dots Z$ - Continuous decision variables to define assignment constraints, used due to the linearization.

Objective Function

The objective of the current problem is to find the optimal assignment of SKUs by minimizing the cycle time of the maximum used picker in the system, ensuring a good balance, in addition to the time related to the tugger train displacement. In this way:

$$Minimize \ Max \left(CT^R, CT^C \right) + T_{tugger} \quad (3.2)$$

The $Max \left(CT^R, CT^C \right)$ function can be easily linearized. This can be done by introducing a continuous decision variable a and applying two constraints (3.4) and (3.5) presented below, making the objective function:

$$Minimize \ a + T_{tugger} \quad (3.3)$$

Constrains

The development of a mixed-integer programming (MIP) operational research model requires the formulation of constraints that accurately represent the problem at hand. In the context of our kitting problem, there are several types of constraints considered to ensure an optimal solution. These constraints are classified into four main categories: consistency constraints, operational constraints, layout constraints and assignment constraints. Each of these constraint types plays a crucial role in defining the variables and the objective function of the MIP model. In this subsection, each of these constraint types is explained in more detail, highlighting their significance and impact on the overall optimization process.

Consistency constraints These constraints ensure the model remains consistent and free of errors, such as ensuring that the values of variables are according to the defined previously.

$$a \geq CT^R \tag{3.4}$$

$$a \geq CT^C \tag{3.5}$$

The constraints described by Inequalities (3.4) and (3.5) establish a relationship between the continuous variable z and the maximum cycle time of the process, considering that the objective function is minimization. The cycle time is determined by two components: the robotic kitting cycle time (CT^R) and the collaborative kitting cycle time (CT^C). The objective of these constraints is to ensure that the value of a is equal to the maximum cycle time between the robotic kitting and collaborative kitting processes. In other words, a should take the value of the higher cycle time to be minimized. To enforce this constraint mathematically, two inequality constraints are specified. The first Constraint (3.4) states that a must be greater than or equal to CT^R, ensuring that a captures the robotic kitting cycle time when it is the higher value. Similarly, the second Constraint (3.5) states that a must be greater than or equal to CT^C, ensuring that a captures the collaborative kitting cycle time when it is the higher value.

$$x_i \in \{0,1\}, \quad \forall i = 1 \dots Z \tag{3.6}$$

The Constraint (3.6) defines the binary type of variable x_i.

Operational constraints These constraints define the performance of the system and are related to the kitting system operations and the functional requirements of the warehouse. In this way, to correctly describe the cycle time of the process, all its operations and steps have to be adequately modeled for both the robotic and collaborative kitting areas.

Robotic Kitting Cycle Time (CT^R)

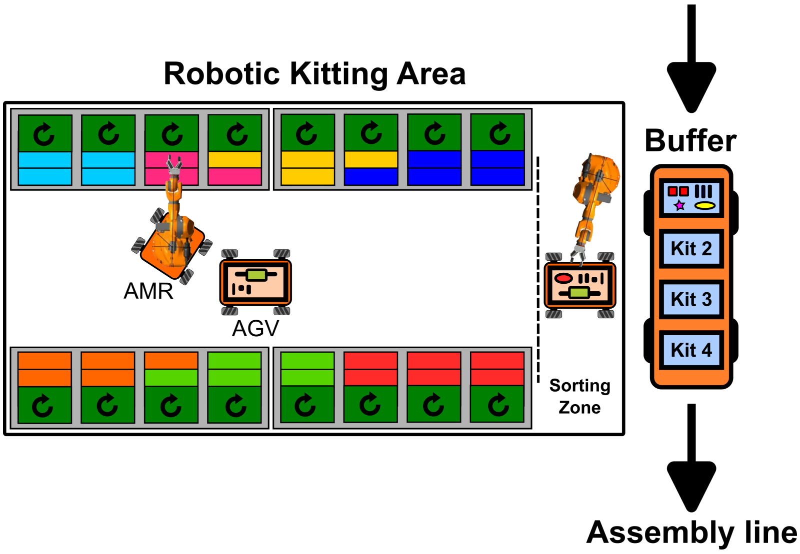


Figure 3.3: Robotic kitting area representation for the AHK System.

An Appendix A has been included in the dissertation to present the main assumptions considered in formulating the cycle time components for the robotic kitting area. These assumptions were derived from discussions with subject matter experts within the company, technological solution experts, information gleaned from scientific literature and documentation such as datasheets, as well as observations of the current kitting processes of the automotive company.

Picking Time (T^R_{pick}):

$$T^R_{pick} = T_{AMR\_picking} \tag{3.7}$$

The Expression (3.7) defines the time related to picking in the robotic kitting area, which includes the AGV picking all parts required for BS EPs and placing them on the AGV box. The number of parts needed (n_i), its frequency in EPs (f_i) and the number of EPs prepared simultaneously (BS) impact this duration. A factor PE_i was added to represent the proportion of failed picks in each SKU i to evaluate the effect of robotic pick ability (also considered equal for both the AMR and the fixed manipulator).

$$T^R_{pick} = \sum_{i=1}^{Z} x_i \cdot T^R_i \cdot n_i \cdot f_i \cdot BS \cdot (1 + PE_i) \tag{3.8}$$

Image Acquisition Time **(T_{image_acq}):**

$$T_{vision} = T_{AMR\_vision} + T_{manipulator\_vision} \tag{3.9}$$

Equation (3.9) defines the duration required for computer vision to capture and process an image, enabling the AMR and manipulator to identify and locate parts within a bin. This information is crucial for selecting the most suitable part, typically the one positioned higher in the bin and closer to the robot. The image acquisition time, as described in Equation (3.10), encompasses the cumulative time for image analysis and acquisition. It is assumed that the time required for the AMR and manipulator to acquire an image is equal ($t_{AMR\_image} = t_{manipulator\_image} = t_{image}$), hence the factor of multiplication by 2. Technological advancements have reduced this time, as the image acquisition process can occur concurrently in the background (represented by the parameter Bg). However, in case of unsuccessful picking attempts, a penalty is incurred, proportional to PE_i, which impacts the overall image acquisition time.

$$T_{image\_acq} = 2 \cdot \sum_{i=1}^{Z} x_i \cdot t_{image} \cdot n_i \cdot f_i \cdot BS \cdot [(1 - Bg) + PE_i] \tag{3.10}$$

AMR Displacement Time **(T_{AMR_disp}):**

$$T_{AMR\_disp} = \frac{d_{AMR\_total}}{AMR \cdot \bar{v}_{AMR}} \tag{3.11}$$

The AMR displacement time in the robotic kitting area, Expression (3.11), refers to the time required for the AMR(s) to traverse the storage area, considering factors such as acceleration, movement through the racks, and deceleration to reach the desired position. The average speed of the AMR, denoted as $\bar{v}_{AMR}$, is determined as the average value between its maximum travel speed considered and the rate of speed change.

The distance traveled by the AMR(s), represented by d_{AMR_total}, is determined in (3.12) by considering the total length of the storage racks. This length is calculated as the sum of the width of each bin, denoted as BW_i, the fixed space size between the bins in the robotic kitting area, represented by S^R, and the empty space in the racks after placing the component bins, represented by the third term in the dividend of Equation (3.12), where it is given by the standard rack length, RL^R, subtracted by the size occupied by the $\lfloor \frac{RL^R}{BW_i} \rfloor$ bins in the rack. The introduction of this last term is an innovative point to add realism to the arrangement of bins on the racks.

The division by the number of levels in the storage racks, denoted as N^R_{levels}, accounts for the vertical arrangement of the bins and the parameter Ps^R plays a crucial role in evaluating the ability of the AMR to pick components from either one side ($Ps^R = 1$) or both sides ($Ps^R = 2$) continuously of the robotic kitting area.

The number of AMRs in the robotic storage area, denoted as AMR, helps reduce the time traveled by each AMR, considering that multiple AMRs are operating in the storage zone and they can be moving to their next picking location allocated to each one in the racks at the same time.

Based on these considerations, the AMR displacement time is calculated by summing the distances traveled for each SKU present in the robotic kitting area that can be picked and dividing by the product of N^R_{levels}, Ps^R, AMR, and $\bar{v}_{AMR}$. This equation provides a quantitative representation of the time required for AMRs to move within the robotic kitting area, considering the dimensions of the storage racks and the characteristics of the speed profile of the AMR.

$$d_{AMR\_total} = \sum_{i=1}^{Z} x_i \cdot \frac{BW_i + S^R + \left(RL^R - \lfloor \frac{RL^R}{BW_i} \rfloor \cdot BW_i\right)}{N^R_{levels} \cdot Ps^R} \tag{3.12}$$

In this way, the AMR displacement time is given by:

$$T_{AMR\_disp} = \sum_{i=1}^{Z} x_i \cdot \frac{BW_i + S^R + \left(RL^R - \lfloor \frac{RL^R}{BW_i} \rfloor \cdot BW_i\right)}{N^R_{levels} \cdot Ps^R \cdot AMR \cdot \bar{v}_{AMR}} \tag{3.13}$$

AGV Displacement Time ($T^R_{AGV\_disp}$):

$$T_{AGV\_disp} = \frac{d_{AGV\_total}}{\bar{v}_{AGV}} \tag{3.14}$$

The AGV displacement in the robotic kitting area is defined using a relation to the AMR displacement, considering that the distance covered is defined between the position of the AMR (where the AGV is near) and the final position located in the sorting zone.

Based on the relationship observed in the Figure 3.4, the average distance traveled by the AGV, denoted as $\bar{d}^R_{AGV}$, is equal to half of its maximum possible distance, represented by $d^R_{AGV\_max}$, as expressed in Equation (3.15).

The maximum distance traveled by the AGV, $d^R_{AGV\_max}$, is determined by a fraction of the maximum distance traveled by the AMR, d_{AMR_total}, where the fraction is given by the parameter F^R that represents the number of facades in the robotic kitting area. When $F^R = 1$ (Figure 3.5a), the maximum distance traveled by the AGV is equal to the one traveled by the AMR, and when $F^R = 2$ (Figure 3.5b),

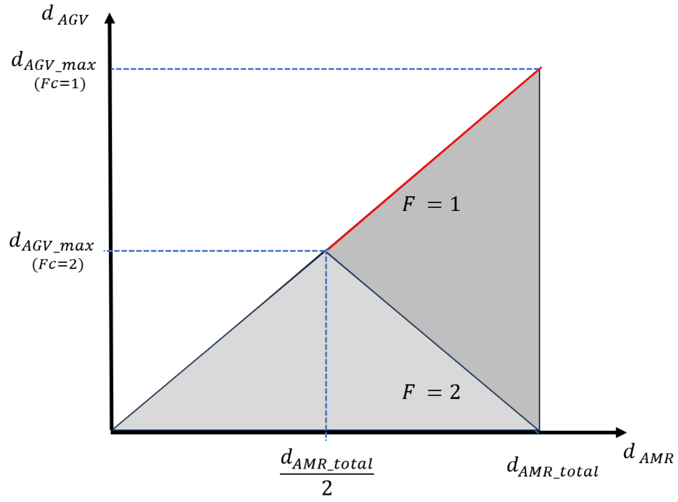
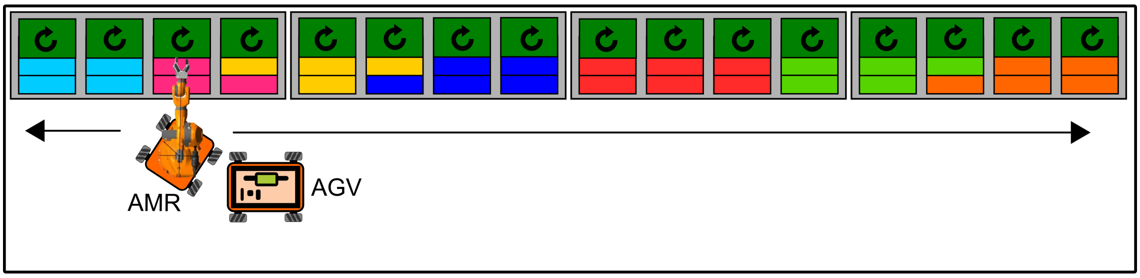
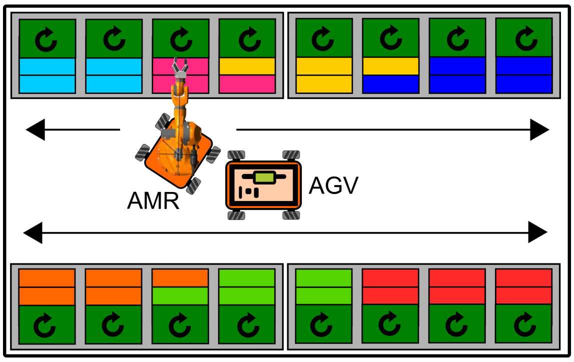


Figure 3.4: Expected relation between AMR and AGV traveled distance in the AHK System.



(a) Warehouse with one facade ($F^R = 1$).



(b) Warehouse with two facades ($F^R = 2$).

Figure 3.5: Practical representation of the number of facades in the robotic kitting area.

it is half of the maximum distance traveled by the AMR, as shown in Equation (3.16).

$$\bar{d}^R_{AGV} = \frac{1}{2} d^R_{AGV\_max} \tag{3.15}$$

$$d^R_{AGV\_max} = \frac{1}{F^R} d_{AMR\_total} \tag{3.16}$$

Considering the distance traveled in the sorting zone, denoted as $Sort^R$, the distance traveled by the AGV, represented by $d^R_{AGV\_total}$, is given by Equation (3.17). This equation accounts for half of the total distance traveled by the AMR divided by F^R, along with the additional distance in the sorting zone.

$$d^R_{AGV\_total} = \frac{d_{AMR\_total}}{2 \cdot F^R} + Sort^R \tag{3.17}$$

Consequently, the time required for the AGV displacement, denoted as $T^R_{AGV\_disp}$, can be calculated by dividing the distance traveled by the AGV by its average speed, $\bar{v}_{AGV}$, as expressed in Equation (3.18). This equation takes into account the distance traveled by the AMR, the number of facades, F^R, and the sorting zone distance $Sort^R$. In this duration, the number of AGVs and the number of AGV trips don't impact $T^R_{AGV\_disp}$ as they are traveling simultaneously to the AMR performing the picking of SKU, and it is referred to the last trip performed by the AGV.

$$T^R_{AGV\_disp} = \frac{1}{\bar{v}_{AGV}} \cdot \left(\frac{d_{AMR\_total}}{2 \cdot F^R} + Sort^R \right) \tag{3.18}$$

To better understand the mathematical reason for this approach, a demonstration is presented in Appendix D.

Empty Bin Removal Time **($T^R_{bin\_rem}$):**

The process of extracting empty bins by the AMR from their storage positions to the evacuation zone for the purpose of replenishing their contents with supplies from external sources is taken into account in the modulation of the cycle time of the kitting system.

The total time needed to remove the empty bins from the storage rack (Equation (3.19)) in the robotic kitting area is given by the number of parts needed (n_i), its frequency in EPs (f_i), the number of EPs prepared simultaneously (BS) and the time of removing each bin individually (t^R_{bin}) which was considered an equal average value for all bins that contain P_i parts of SKU i. The factor PE_{bin} represents the proportion of failed picks, i.e., the picking error associated with the empty bins. As it was considered that the evacuation zone is positioned permanently on the third level of the storage rack, no travel time is needed to remove the bins.

$$T^R_{bin\_rem} = \sum_{i=1}^{Z} x_i \cdot t^R_{bin} \cdot \frac{n_i \cdot f_i \cdot BS}{P_i} \cdot (1 + PE_{bin}) \tag{3.19}$$

Sorting Time (T_{sort}):

The sorting time consists of a fixed manipulator picking parts from the AGV and placing them on the correct kit box in the tugger train in the sorting area (Equation (3.20)). t^R_s defines the average sorting time to pick and place a single part of SKU i in the correct kit box. The factor PE_{sort} represents the proportion of failed picks, i.e., the error associated with the manipulator when it fails to pick parts and Col is a parameter representing a delay/waiting time in the manipulator movement due to the sorting process occurring in a collaborative way with the operator also sorting components to complete the kits.

$$T^R_{sort} = \sum_{i=1}^{Z} x_i \cdot t^R_s \cdot n_i \cdot f_i \cdot BS \cdot (1 + PE_{sort} + Col) \tag{3.20}$$

Packaging Removal Time (T_{pack_rem}):

The total time needed to remove the packaging items that protect the SKUs from handling damage. These packaging items, as suggested in research (Boudella et al., 2018) and industry experts, include cardboard dividers, foam and cardboard interlayer sheets, and plastic bags, commonly used in the automotive industry. In the case of robotic manipulators, is considered that the fixed manipulator only can remove the uniform shape and size packages, being the interlayer sheets and dividers (Equation (3.21)), which demands that the human operator at the collaborative kitting area to pick components with other packaging items.

$$T^R_{pack\_rem} = T^R_{interlayer} + T^R_{divider} \tag{3.21}$$

For each SKU i bin, it is considered the time needed for the manipulator to remove one interlayer sheet, t^R_{IL}, for all the IL_i sheets in the bin of SKU i. An interlayer sheet picking failure rate ($PE_{interlayer}$) is associated with the picking capability of this material.

$$T^R_{interlayer} = \sum_{i=1}^{Z} x_i \cdot \frac{n_i \cdot f_i \cdot BS}{P_i} \cdot \left[IL_i \cdot t^R_{IL} \cdot (1 + PE_{interlayer}) \right] \tag{3.22}$$

For each SKU i bin, it is considered the time needed for the manipulator to remove one divider (t^R_D) for all the D_i dividers in the bin of SKU i. A divider picking failure rate ($PE_{divider}$) is associated with the picking capability of this material.

$$T^{R}_{divider} = \sum_{i=1}^{Z} x_i \cdot \frac{n_i \cdot f_i \cdot BS}{P_i} \cdot \left[D_i \cdot t^{R}_{D} \cdot (1 + PE_{divider}) \right] \tag{3.23}$$

Consequently:

$$T^{R}_{pack\_rem} = \sum_{i=1}^{Z} x_i \cdot \frac{n_i \cdot f_i \cdot BS}{P_i} \cdot \left[IL_i \cdot t^{R}_{IL} \cdot (1 + PE_{interlayer}) + D_i \cdot t^{R}_{D} \cdot (1 + PE_{divider}) \right] \tag{3.24}$$

Gripper Change Time ($T_{gripper}$):

$$T_{gripper} = 2 \cdot T_{gripper\_pick} + T_{gripper\_pack} + T_{gripper\_bin} \tag{3.25}$$

The time related to the operation of the gripper changing in the AGV and the fixed manipulator, presented in Equation (3.25), refers to the duration required to replace the end effector of the manipulator, which is the component responsible for holding and manipulating the objects. The gripper change time includes disconnecting the current end effector, connecting the new end effector, and any additional time required to calibrate or adjust the new end effector. This time is an essential factor to consider in optimizing the overall cycle time of a manipulator and has an impact on the efficiency and productivity of the system. It is present in three different situations: the gripper change needed before picking a certain part (1), the gripper change before removing an empty bin (2), and the gripper change before removing packaging items (3), where the AGV deals with all three parameters but the sorting manipulator only proceeds with the operation (1). To define this parameter, it was considered in Expression (3.25) that the time needed to change the gripper to pick different components is the same for both the AMR and the fixed manipulator ($T_{AGV\_gripper\_pick} = T_{manipulator\_gripper\_pick} = T_{gripper\_pick}$). In this way, the first term is multiplied by a factor 2.

$$T_{gripper\_pick} = \sum_{i=1}^{Z} x_i \cdot f_i \cdot BS \cdot t_{gripper\_parts} \cdot (1 + Cal) \cdot AR_{parts} \tag{3.26}$$

The Expression (3.26) defines the total time needed to change the gripper before picking parts, where it considers the time needed for a single tool change before picking a part where is as an impact of a parameter Cal representing the fraction of time incremented to calibrate/adjust the end effector, for all $f_i \cdot BS$ occurrences.

Incorporating storage assignment rules may aid in enhancing the efficiency of tool changes by grouping SKUs that can be picked with the same tool. This can be quantified by AR_{parts}, which signifies the proportion of time reduction of the preparation cycle that requires a tool change can be reduced by grouping in the picking process components that can be picked by the same gripper, reducing setup times.

$$T_{gripper\_pack} = \sum_{i=1}^{Z} x_i \cdot \frac{n_i \cdot f_i \cdot BS}{P_i} \cdot (IL_i + D_i) \cdot t_{gripper\_pack} \cdot (1 + Cal) \cdot AR_{pack} \quad (3.27)$$

Regarding the case of gripper change to remove the packaging of the parts (Expression (3.27)), an analogous method was considered, differing in the fact that it considered the average number of bins, including the number of components for SKU i, n_i, and the number of parts of SKU i in a bin, and applied before every IL_i interlayers and D_i dividers. This value is slightly improved if we have an efficient assignment rule for inner packaging removal, letting $AR_{pack} < 1$.

$$T_{gripper\_bin} = \sum_{i=1}^{Z} x_i \cdot \frac{n_i \cdot f_i \cdot BS}{P_i} \cdot t_{gripper\_bin} \cdot (1 + Cal) \cdot AR_{bins} \quad (3.28)$$

Finally, to describe the time needed to remove empty bins (Expression (3.28)), the analogous method was also used, considering the time for a single empty bin removal gripper change, $t_{gripper\_bin}$, for all the number of empty bins removed during the preparation of BS EPs. An efficient assignment rule to remove empty bins consecutively can also reduce this time, represented by AR_{bins} parameter.

In this way, the total time needed to change grippers is defined by:

$$\begin{aligned} T_{gripper} = (1 + Cal) \sum_{i=1}^{Z} x_i \cdot f_i \cdot BS \, \big[2 \cdot t_{gripper\_parts} \cdot AR_{parts} + \\ + \frac{n_i}{P_i} \left((IL_i + D_i) \cdot t_{griper\_pack} \cdot AR_{pack} + t_{gripper\_bin} \cdot AR_{bins} \right) \big] \end{aligned} \quad (3.29)$$

Considering the previously presented operations, the cycle time for the robotic kitting area CT^R, in the AHK System, to prepare BS EPs is given by:

$$\begin{aligned} CT^R = T^R_{pick} + T_{image\_acq} + T_{AMR\_disp} + T^R_{AGV\_disp} + \\ + T^R_{bin\_rem} + T^R_{sort} + T^R_{pack\_rem} + T_{gripper} \end{aligned} \quad (3.30)$$

Collaborative Kitting Cycle Time (CT^C)

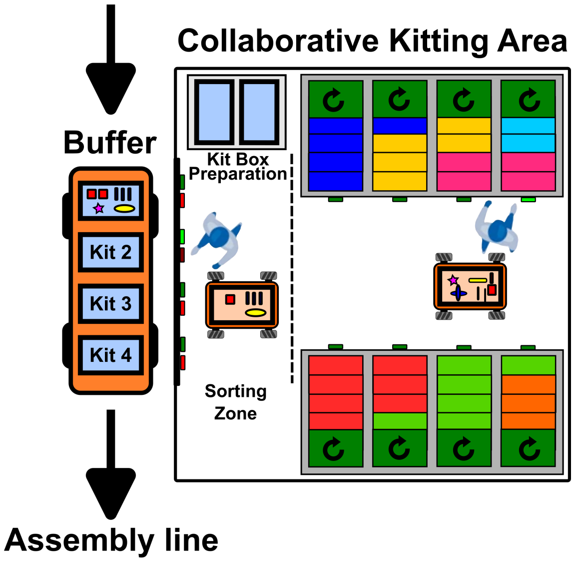


Figure 3.6: Collaborative kitting area representation for the AHK System.

To define and obtain the following kitting cycle time parameters of the collaborative kitting area, a set of assumptions was considered and are presented in Appendix B. These assumptions made for the collaborative kitting area are analogous to those made for the robotic kitting area. They were based on discussions with experts in the technological solutions to be implemented in the warehouse of the company addressed in this work, information extracted from scientific literature and technical documentation such as datasheets, and observations of the company's current kitting processes.

Kit Box Preparation Time (T_{kit_prep}):

The kit box preparation time refers to the duration required for the initial setup of empty kit boxes within the tugger train, enabling the commencement of the kitting process in both the robotic and collaborative kitting areas. This process involves an operator in the sorting area retrieving empty kit boxes and correctly positioning them within the designated slots of the tugger train. The kit preparation time encompasses the activities of picking the empty kit boxes and ensuring their proper placement by the operator, ensuring readiness for subsequent fulfillment of the BOM for each respective kit.

$$T_{kit\_prep} = N_{kits} \cdot t_{kp} \cdot (1 - Ef_{kit\_prep}) \tag{3.31}$$

Equation (3.31) determines the total kit box preparation time by multiplying the number of kits (N_{kits}) by the average time to place one kit box (t_{kp}). The term $(1 - Ef_{kit\_prep})$ adjusts the duration based on the efficiency of the process, resulting in a reduction of the total time accordingly. This parameter accounts for factors such as the ability of the operator to handle multiple kit boxes simultaneously, streamlining the process and reducing the overall duration of kit box preparation.

Pick-to-Light System Identification Time (T_{p2l}):

$$T_{pick2light} = T_{p2l\_data} + T_{p2l\_operator} \tag{3.32}$$

The pick-to-light system identification time refers to the duration required for the system to identify and activate the appropriate pick-to-light indicators associated with specific items or locations in a warehouse or picking area. This process involves the communication between the system and the pick-to-light modules, which are equipped with visual indicators such as lights or displays.

During the identification time, the system processes relevant SKU information. The system then sends signals to the pick-to-light modules, identifying and activating the appropriate pick-to-light indicators associated with specific items and/or locations in the warehouse picking area. This process involves the communication between the system and the pick-to-light modules through gateways.

During this operation, according to the technology experts, the system retrieves information about the items to be picked, such as their location, quantity, or specific order details. The system then sends data packages with commands to the pick-to-light modules, which illuminate or display the corresponding indicators to guide the operator to the correct item and location for picking, represented in Equation (3.32) by T_{p2l_data}.

The identification time depends on various factors, including the complexity of the system, the responsiveness of the communication network, and the efficiency of the pick-to-light modules themselves, such as the battery and the proximity sensor to detect the respective picking, and the identification by the operator of the illuminated devices to identify the need for picking of the respective parts, represented by $T_{p2l\_operator}$. It may also be influenced by the number of items or locations to be identified and the sophistication of the identification algorithms employed.

According to the development team of the pick-to-light system in the project, if the proximity sensor fails to detect the picking of at least one component, whether due to an actual miss or a sensor failure, the picking order remains open. In a warehouse installation, multiple gateways are installed to provide redundancy in message delivery to the pick-to-light devices.

In the proximity sensor of the respective modules, false negatives (when the operator passes their hand, but the module fails to recognize the picking) have a very low probability of occurrence. However, false positives (when the module incorrectly considers a picking without the operator's hand passing through) may occur with higher probability. The technology offers high flexibility, particularly in the versatility of changing the module's batteries.

Regarding error correction, the system implementation allows for notifying the operator to pick the missing components or if any incorrect piece has been collected, enhancing the overall reliability and accuracy of the pick-to-light process.

$$T_{p2l} = t_{p2l} \cdot (1 + EC_{com}) + \sum_{i=1}^{Z} (1 - x_i) \cdot t_{obs} \cdot (1 + EC_{obs} + EC_{detect}) \tag{3.33}$$

The Equation (3.33) represents the pick-to-light system identification time, which consists of two main components: the system communication time (T_{p2l_data}) and the operator observation time ($T_{p2l\_operator}$).

The first part of the equation, represented by $t_{p2l} \cdot (1 + EC_{com})$, accounts for the time required for the system to send data packages to the pick-to-light modules. This time includes the transmission time and any potential delays due to communication errors. The parameter EC_{com} represents the error correction factor, indicating the additional time needed if a new data package must be sent due to devices not acknowledging the initial transmission.

The second part of the equation, $\sum_{i=1}^{Z}(1 - x_i) \cdot t_{obs} \cdot (1 + EC_{obs} + EC_{detect})$, relates to the time spent by the operator in observing and responding to the pick-to-light modules. The term $(1 - x_i)$ represents the absence of robotic picking for SKU i, indicating that it is the responsibility of the operator. The observation time by the operator, denoted by t_{obs}, accounts for the time it takes for the operator to identify a pick-to-light module turned on, indicating the need for picking. This time is influenced by the parameter EC_{obs}, which reflects any additional time required if the operator fails to observe a turned-on module. Additionally, the parameter EC_{detect} represents the potential delay if the pick-to-light module proximity sensor leads to the light of the module being turned off incorrectly without the operator picking the respective part.

The equation provides a comprehensive representation of the pick-to-light system identification time, considering both the communication aspect of the system, the observation by the operator, and the response time, being crucial for optimizing order fulfillment processes, reducing picking errors, and improving overall operational efficiency in the warehouse environment.

Picking Time (T^{C}_{pick}):

The picking time in the collaborative kitting area refers to the duration required for the operator to retrieve components from the designated bins within the racks and subsequently place them in the nearby AGV. This process involves the manual selection by the operator and handling of the components.

During the picking operation, the operator accesses the bins in the racks and identifies the specific components needed based on the provided instructions in the BOM and by the pick-to-light system. The operator then physically retrieves the components from the bins, ensuring accuracy and precision in the selection.

Once the components are obtained, the operator places them in the AGV located in close proximity for further transportation and sorting.

The picking time in the collaborative kitting area is influenced by various factors such as the layout and organization of the bins, the size and weight of the parts, the ergonomics of the components, and the efficiency and experience of the operator. It is crucial to optimize this picking process to minimize the cycle time and enhance productivity.

$$T^C_{pick} = \sum_{i=1}^{Z}(1 - x_i) \cdot t^C_i \cdot \frac{n_i \cdot f_i \cdot BS}{sim_i} \tag{3.34}$$

Equation (3.34) represents the determination of this picking process performed by the operator, where the term t^O_i represents the time needed for the operator to perform a single pick and place operation for a component belonging to SKU i. The remaining factors in the equation are related to the characteristics of SKU i. These include n_i, which represents the total number of components required for SKU i in a single batch or order. The frequency of usage f_i denotes how often SKU i is required. The batch size BS indicates the number of units produced simultaneously.

Finally, to consider the maximum number of components of SKU i that the operator can pick simultaneously, the parameter sim_i was added. This value is limited by factors such as the dexterity of the operator, the size and weight of the components, and other operational considerations. It ranges from 1 to $n_i \cdot f_i \cdot BS$, meaning the operator can pick anywhere from a single component to the entire set of SKU i needed at once (Expression (3.35)).

$$sim_i \in [1; n_i \cdot f_i \cdot BS] \tag{3.35}$$

Operator Displacement Time (T^C_{disp} **):**

$$T^C_{disp} = \frac{d^C_{total}}{OP \cdot \bar{v}_{OP}} \tag{3.36}$$

Analogously to the robotic kitting area, in order to determine the time taken by the human operator(s) to move within the collaborative kitting area, several factors need to be considered, such as the distance traveled by the operator(s), the number of operators working and the average velocity v^O_{avg}, that should be defined as the average value between his maximum working speed and the rate of speed change (which includes in initial speed until reaching the limit speed and the same for stopping).

$$d^C_{total} = \sum_{i=1}^{Z} (1 - x_i) \cdot \frac{BW_i + S^C + \left(RL^C - \lfloor \frac{RL^C}{BW_i} \rfloor \cdot BW_i\right)}{N^C_{levels} \cdot Ps^C} \tag{3.37}$$

The Equation (3.37) represents the determination of the total distance traveled by the human operator(s) within the collaborative kitting area. The distance is determined by considering the length of the storage racks, which is a combination of the size of each bin of SKU i, denoted as BW_i, the fixed space size between the bins, represented by S^C, and the empty space in the racks after placing the component bins, where it is given by the standard rack length in the collaborative kitting area, RL^C subtracted by the size occupied by the $\lfloor \frac{RL^C}{BW_i} \rfloor$ bins in the rack. The division by the number of levels in the racks, denoted as N^C_{levels}, considers the vertical arrangement of the bins.

Additionally, the parameter Ps^C plays a crucial role in evaluating the ability of the operator to pick components from either one side ($Ps^C = 1$) or both sides ($Ps^C = 2$) of the collaborative area, where it depends on the number of facades in the warehouse with the relation presented in the Expression (3.38).

$$\begin{cases} F^C = 1 \Rightarrow Ps = 1 \\ F^C = 2 \Rightarrow Ps = 1 \text{ or } 2 \end{cases} \tag{3.38}$$

Lastly, the number of human operators in the storage area, denoted as OP, is included to account for the reduction of the distance traveled by each operator to pick components. By considering these factors, the equation provides a quantitative representation of the distance covered by the human operator(s) in the collaborative kitting area.

In this way, the operator(s) displacement time is given by:

$$T_{OP\_disp} = \sum_{i=1}^{Z} (1 - x_i) \cdot \frac{BW_i + S^C + \left(RL^C - \lfloor \frac{RL^C}{BW_i} \rfloor \cdot BW_i\right)}{N^C_{levels} \cdot Ps^C \cdot OP \cdot \bar{v}_{OP}} \tag{3.39}$$

AGV Displacement Time $(T^C_{AGV\_disp})$**:**

$$T^C_{AGV\_disp} = \frac{d_{AGV\_total}}{\bar{v}_{AGV}} \tag{3.40}$$

The definition of AGV displacement time, in the collaborative kitting area, is defined similarly to the AGV displacement time presented in the robotic kitting zone, where the distance covered is defined between the position of the human operator(s) (where the AGV is near) and the final position in the sorting zone.

The determination of the total distance traveled by AGV can be explained by considering its relationship with the total distance traveled by the human operator(s) in the collaborative kitting area, as shown in Figure 3.7.

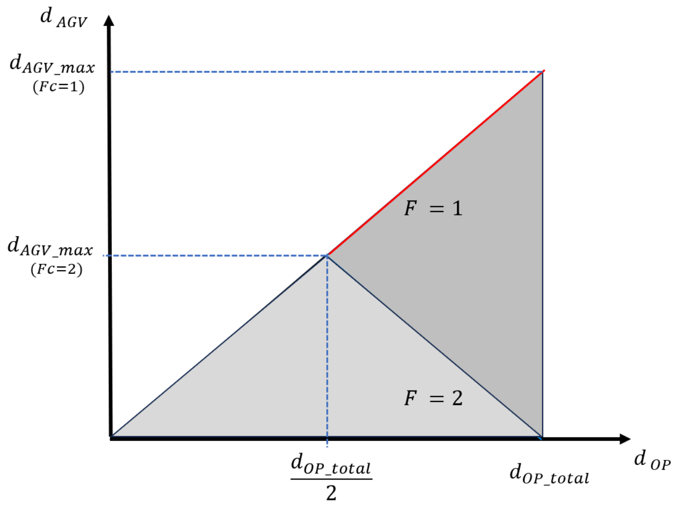


Figure 3.7: Expected relation between Operator and AGV traveled distance in the AHK System.

Based on this relationship, it is observed that the average distance traveled by the AGV, denoted as $\bar{d}^C_{AGV}$, is equal to half of its maximum possible distance, represented by $d^C_{AGV\_max}$, as expressed in Equation (3.41).

The maximum distance traveled by the AGV, $d^C_{AGV\_max}$, is determined by a fraction of the maximum distance traveled by the human operator, d_{OP_total}, where the fraction is given by the parameter F^C. When $F^C = 1$, the maximum distance traveled by the AGV is equal to the one traveled by the operator, and when $F^C = 2$, it is half of the maximum distance traveled by the operator, as shown in Equation (3.42). A detailed explanation can be found in Appendix D.

$$\bar{d}^C_{AGV} = \frac{1}{2} d_{AGV\_max} \tag{3.41}$$

$$d^C_{AGV\_max} = \frac{1}{F^C} d_{OP\_total} \tag{3.42}$$

Considering the distance traveled in the sorting zone, denoted as $Sort^C$, the total distance traveled by the AGV, represented by $d^C_{AGV\_total}$, is given by Equation (3.43). This equation accounts for half of the total distance traveled by the operator divided by F^C plus the additional distance in the sorting zone.

$$d^C_{AGV\_total} = \frac{d_{OP\_total}}{2 \cdot F^C} + Sort^C \tag{3.43}$$

Consequently, the time required for the AGV displacement, denoted as $T^C_{AGV\_disp}$, can be calculated by dividing the total distance traveled by the AGV by its average speed, $\bar{v}_{AGV}$, as expressed in Equation (3.44). This equation takes into account the total distance traveled by the operator, the fraction F^C, and the sorting zone distance $Sort^C$. As for the robotic kitting area, the number of AGVs and the number of AGV trips don't impact $T^C_{AGV\_disp}$ it refers to the last trip performed by the AGV.

$$T^C_{AGV\_disp} = \frac{1}{\bar{v}_{AGV}} \cdot \left(\frac{d_{OP\_total}}{2 \cdot F^C} + Sort^C \right) \tag{3.44}$$

Empty Bin Removal Time **($T^C_{bin\_rem}$)**:

$$T^C_{BinRemoval} = T^O_{remove\_bin} \tag{3.45}$$

The empty bin removal time in the collaborative kitting area (Expression (3.45)) is a process analogous to the one observed in the robotic kitting area. It involves the time required for the operator to effectively remove an empty bin from its designated location in the storage rack and dispose of it at the nearest evacuation ramp.

The total time needed for empty bin removal from the storage rack, as represented by Equation (3.46), takes into account various factors. These include the number of parts needed (n_i), the frequency of the parts in the EPs (f_i), the number of EPs prepared simultaneously (BS), and the time required to remove each bin individually (T^O_B). The average removal time, denoted as T^O_{bin}, is assumed to be the same for all bins containing P_i parts of SKU i. It is important to note that in the collaborative kitting area, it is assumed that operators do not fail to pick empty bins.

$$T^C_{bin\_rem} = \sum_{i=1}^{Z} (1 - x_i) \cdot t^C_{bin} \cdot \frac{n_i \cdot f_i \cdot BS}{P_i} \tag{3.46}$$

Sorting Time **(T^C_{sort})**:

The sorting process involves the task of a human operator picking parts from the AGV, which is filled with components for the different kits, and placing them correctly in the corresponding kit boxes on the tugger train, completing the kits already being filled by the fixed manipulator from the robotic kitting area. The sorting time, represented by Equation (3.47), captures the duration required for the operator to perform this picking and placing operation.

In the equation, t^C_s denotes the average time needed for the operator to sort and place a single part of SKU i into the correct kit box. Similar to the picking time, the parameter sim_i is used to consider the maximum number of components of SKU i that the operator can pick simultaneously.

It is assumed that there are no errors made by the operator picking components during the sorting process. However, to account for the possibility of incorrectly placed parts from both the operator and the fixed manipulator, the term EC_{sort} is introduced as an error correction parameter. This parameter represents the time required for the operator to rectify any mistakes by picking a wrongly placed part from one kit box and relocating it to the correct kit box, following a quality control procedure.

$$T^{C}_{sort} = \sum_{i=1}^{Z} (1 - x_i) \cdot t^{C}_{s} \cdot \frac{n_i \cdot f_i \cdot BS}{sim_i} \cdot (1 + EC_{sort}) \tag{3.47}$$

By employing this equation, The sorting time, denoted as $T^{O}_{sorting}$, is obtained quantitatively by summing the sorting times for each SKU i from 1 to C, multiplied by the respective number of parts, their frequency, the number of EPs, and the correction error parameter.

Packaging Removal Time ($T^{C}_{pack\_rem}$):

$$T^{C}_{pack\_rem} = T^{C}_{interlayer} + T^{C}_{divider} + T_{foam} + T_{plastic\_bags} \tag{3.48}$$

The packaging removal process in the collaborative kitting area involves several tasks (Expression (3.48)), including the removal of various packaging materials such as interlayer sheets, which are used to separate individual components, dividers, foam protections, and plastic bags that may enclose the components. The objective is to discard these packaging components into a designated container for disposal.

During the removal process, the operator is responsible for identifying and removing the cardboard dividers, foam, interlayer sheets, and plastic bags from the bins and components. This step ensures that only the desired components go to the kit boxes, while the packaging materials are set aside for proper disposal.

Once the packaging materials are removed, the operator must travel to the designated container for their disposal in an appropriate and environmentally friendly manner.

The packaging removal process is an integral part of the collaborative kitting area, as it ensures the effective and efficient handling of packaging materials, keeping the work environment clean and organized. By adhering to proper packaging removal procedures, it maintains a streamlined workflow in the production line and promotes environmental awareness through responsible waste and product management.

$$T^C_{pack\_rem} = \sum_{i=1}^{Z}(1-x_i)\cdot\frac{n_i\cdot f_i\cdot BS}{P_i\cdot sim_{pack}}\cdot\left[IL_i\cdot t^C_{IL}+D_i\cdot t^C_D+Fo_i\cdot t_F+PB_i\cdot t_{PB}\right] \tag{3.49}$$

The equation for the packaging removal time, as described by Equation (3.49), quantifies the time required for the human operator to complete the process of removing packaging materials in the collaborative kitting area.

In the equation, various parameters are considered to calculate the packaging removal time. These parameters include the characteristics of each SKU bin, such as the number of interlayer sheets (IL_i), dividers (D_i), foam protections (Fo_i), and plastic bags (PB_i) associated with the bin of SKU i. Additionally, factors like the number of parts needed (n_i), their frequency of usage (f_i), and the number of EPs produced simultaneously (BS) are taken into account.

The packaging removal time for each SKU bin is computed by multiplying the respective quantities of interlayer sheets, dividers, foam protections, and plastic bags by their corresponding removal times (t^C_{IL}, t^C_D, t_F and t_{PB}, respectively). This accounts for the effort required to remove each packaging component. The summation across all SKUs from 1 to C ensures that the packaging removal time is calculated for all relevant bins.

Furthermore, the factor sim_{pack} represents the adjustment factor considering the maximum number of packages that the operator can handle simultaneously, accounting for the efficiency of the packaging removal process.

By using this equation, one can accurately estimate the total time required for the human operator to complete the packaging removal process in the collaborative kitting area, taking into account the specific characteristics of each SKU bin and the relevant parameters that influence the process.

Given the previously presented operations for the collaborative kitting area, the cycle time CT^C, in the AHK System, to prepare BS EPs is given by:

$$\begin{aligned} CT^C = {} & T_{kit\_prep}+T_{p2l}+T^C_{pick}+T_{OP\_disp}+T^C_{AGV\_disp}+ \\ & +T^C_{bin\_rem}+T^C_{sort}+T^C_{pack\_rem} \end{aligned} \tag{3.50}$$

Tugger Train (Buffer) The tugger train system plays a crucial role in the AHK System layout, serving as a buffer zone where the kits being assembled are temporarily maintained before being transported to the BoL. In this context of the automotive production process, various components and parts are assembled into these kits and are used in specific workstations. The tugger train system acts as a reliable intermediary, efficiently managing the flow of kits between the warehouse and the BoL where they are needed in different assembly stations. This ensures a steady supply of kits, enabling smooth operations and minimizing downtime. In this way, it becomes essential to analyze and define the time required for the tugger train to complete its trips, considering factors such as trip duration, number of kits to transport, and the availability of tugger trains in the smart factory system. To model the time for the tugger train to deliver the kits, a set of assumptions were considered and presented in Appendix C.

In a cycle time, the tugger train transports the already assembled kits to the line side where the required kits are retrieved at the same time that the following kits are being mounted. Due to this fact, only the time needed to perform the final tugger train trip, containing the last kit boxes to be delivered, impacts the total cycle time of the kitting operations. This duration is defined in Equation (3.51), taking into account the travel time considering no stops at the destination stations on the BoL, T_{run}, and the time required for the tugger train to stop, t_{stop}, for all the N_{kits} required stops.

$$T_{tugger} = T_{run} + t_{stop} \cdot N_{kits} \tag{3.51}$$

For analysis purposes, the total time required for tugger train trips can be easily obtained with Equation (3.52) by multiplying T_{tugger} by the number of trips required for the tugger train to deliver all kits, represented by $N_{tugger\_train\_trips}$ and accounting for the number of tugger trains available, $TUGGER$.

$$T_{tugger\_total} = \frac{N_{tugger\_train\_trips} \cdot \left(T_{run} + t_{stop} \cdot N_{kits}\right)}{TUGGER} \tag{3.52}$$

This innovative consideration of the distance traveled by tugger train and time factors contributes to a more accurate evaluation of system performance. By incorporating these aspects into the analysis, it becomes possible to identify potential bottlenecks, understand the tugger train impact, and enhance overall system productivity. Thus, this explicit characterization of the tugger train's role is a valuable addition to the analysis of the kitting system.

$$N^{R}_{AGV\_trips} \geq \frac{\sum_{i=1}^{Z} x_i \cdot n_i \cdot f_i \cdot BS \cdot M_i}{M_{AGV}} \tag{3.53}$$

$$N^{R}_{AGV\_trips} \geq \frac{\sum_{i=1}^{Z} x_i \cdot n_i \cdot f_i \cdot BS \cdot Vol_i}{Vol_{AGV}} \tag{3.54}$$

$$N^{C}_{AGV\_trips} \geq \frac{\sum_{i=1}^{Z} (1 - x_i) \cdot n_i \cdot f_i \cdot BS \cdot M_i}{M_{AGV}} \tag{3.55}$$

$$N^{C}_{AGV\_trips} \geq \frac{\sum_{i=1}^{Z} (1 - x_i) \cdot n_i \cdot f_i \cdot BS \cdot Vol_i}{Vol_{AGV}} \tag{3.56}$$

Inequality (3.53) represents the constraint for AGV container weight capacity in the robotic kitting area. It ensures that the number of AGV trips, denoted by

$N^{R}_{AGV\_trips}$, is at least equal to the total weight of parts to be transported in this area divided by the maximum weight capacity of the AGV, M_{AGV}. Similarly, Constraint (3.56) guarantees that the weight of the parts does not exceed the AGV capacity in the collaborative kitting area.

In other way, Inequalities (3.54) and (3.56) represent the constraints for AGVs containers volume capacity. It ensures that the number of AGV trips is sufficient to accommodate the total volume of parts to be transported in both the robotic and collaborative kitting areas, divided by the maximum volume capacity of the AGV, Vol_{AGV}. These constraints ensure that the volume of the parts does not exceed the capacity of the AGV in the kitting areas.

$$N_{kits} \geq \frac{\sum_{i=1}^{Z} n_i \cdot f_i \cdot BS \cdot M_i}{M_{kit}} \tag{3.57}$$

$$N_{kits} \geq \frac{\sum_{i=1}^{Z} n_i \cdot f_i \cdot BS \cdot Vol_i}{Vol_{kit}} \tag{3.58}$$

$$N_{tugger\_train\_trips} \geq \frac{N_{kits}}{N_{kits\_MAX}} \tag{3.59}$$

Inequalities (3.57) and (3.58) represent the constraints for kit box weight capacity and volume capacity, respectively, to determine the number of kit boxes needed. These constraints ensure that the number of kit boxes, denoted by N_{kits}, is at least equal to the total weight divided by the maximum weight capacity of a kit box, M_{kit}, and the total volume of SKUs divided by the maximum volume capacity of a kit box, Vol_{kit}, guaranteeing that the weight and volume of the parts assigned to each kit box do not exceed their respective capacities.

Lastly, Inequality (3.59) represents the constraint for tugger train capacity, to determine the number of tugger train trips. It ensures that the number of tugger train trips, denoted by $N_{tugger\_train\_trips}$, is at least equal to the total number of kit boxes divided by the maximum kit loading capacity of the tugger train, N_{kits_MAX}. This constraint ensures that the tugger train can accommodate all the required kit boxes.

By incorporating these operational constraints into the model, the number of AGV trips, kit boxes, and tugger train trips can be determined based on the weight and volume capacities of the AGV, kit boxes, and tugger train, respectively.

Layout constraints These are constraints that limit the performance of the system and are related to the physical limitations of the warehouse such as the space available to store the parts of the different SKUs.

$$\sum_{i=1}^{i=C}\left[x_i \cdot \frac{\left(AW^R + F^R \cdot RD^R\right) \cdot \left(BW_i + S^R\right)}{N^R_{levels}} + \right. \\ \left. + (1 - x_i) \cdot \frac{\left(AW^C + F^C \cdot RD^C\right) \cdot \left(BW_i + S^C\right)}{N^C_{levels}}\right] \leq A \tag{3.60}$$

$$Vol_{buffer} \geq N_{kits} \cdot Vol_{\text{kit}} \tag{3.61}$$

The layout constraint described by Inequality (3.60) pertains to the space occupation by the hybrid kitting system. It ensures that the total occupied space of the system, calculated on the left-hand side of the equation, for two terms: one for the robotic kitting area and another for the manual kitting area, does not exceed the available space of the warehouse denoted by the variable A on the right-hand side.

In this Inequality (3.60), four parameters are introduced to represent different dimensions and characteristics of the kitting system: RD^R, RD^C, AW^R, and AW^C. These parameters correspond to the depth of a rack in the robotic kitting area, the depth of a rack in the collaborative kitting area, the width of the aisle in the robotic kitting area, and the width of the aisle in the collaborative kitting area, respectively. For the robotic kitting area, the occupied space is determined by the product between the warehouse width (given by the width of the aisle, AW^R, and the total depth of the racks, $F^R \cdot RD^R$) and the warehouse length (given by the width of the bin of SKU i, BW_i, and the spacing between bins, S^R), divided by the number of levels in the racks, N^R_{levels}, for all the SKUs allocated in the robotic area. For the collaborative kitting area, the space occupied is determined analogously for all the SKUs allocated in this area.

In Constraint (3.61), the buffer volume determines the total volume of kits that are prepared and sent via tugger train from this area. The volume of kits passing through the buffer should be greater than or equal to the product of the desired number of kits mounted, N_{kits}, and the volume of a single kit, represented by Vol_{kit}. This constraint ensures that the buffer has sufficient capacity to hold the needed volume of kits transported.

Assignment constraints These constraints are related to the assignment of resources to tasks and can include limitations on the machines available for a certain task.

$$\text{If } PB_i > 0 \text{ or } Fo_i > 0 \text{ or } Feas_i = 0 \text{ then } x_i = 0, \quad \forall i = 1 \ldots Z \tag{3.62}$$

Constraint (3.62) should be linearized in order to be applied to the MIP model. This linearization can be easily performed by introducing one auxiliary binary variable, b_i, and the following inequalities (cf. Boudella et al. (2018)):

$$PB_i \leq L \cdot b_i, \quad \forall i = 1 \ldots Z \tag{3.63}$$

$$Fo_i \leq L \cdot b_i, \quad \forall i = 1 \ldots Z \tag{3.64}$$

$$Feas_i \geq 1 - b_i, \quad \forall i = 1 \ldots Z \tag{3.65}$$

$$x_i \leq 1 - b_i, \quad \forall i = 1 \ldots Z \tag{3.66}$$

$$b_i \in \{0, 1\}, \quad \forall i = 1 \ldots Z \tag{3.67}$$

The assignment constraints described by Inequalities (3.63), (3.64), and (3.65) capture the conditions that determine whether a part can be allocated to the robotic kitting area or if it must be assigned to the collaborative kitting area. These constraints consider factors such as the presence of plastic bags, foam interlayers, and the feasibility of robotic picking.

Constraint (3.63) addresses the presence of plastic bags. The term Pb_i represents the number of plastic bags per bin associated with SKU i, and L is a large positive constant. The constraint states that if a part has plastic bags ($Pb_i > 0$), then it cannot be allocated to the robotic kitting area ($b_i = 1$ and $x_i = 0$, through Constraint (3.66)). If an SKU doesn't have plastic bags ($Pb_i = 0$), so x_i can be zero or one.

Constraint (3.64) deals with foam interlayers. The term FL_i represents the number of foam interlayers associated with SKU i. The constraint states, analogously to the previous constraint, that if a part has foam interlayers ($FL_i > 0$), it must be assigned to the collaborative kitting area ($x_i = 1$). This ensures that SKUs requiring foam interlayers are not allocated to the robotic kitting area.

Constraint (3.65) addresses the feasibility, $Feas_i$, of robotic picking for a given SKU, due to factors such as the positioning of parts in the bins, shape, or material constitution. If $Feas_i = 1$, it means that SKU i is suitable for robotic picking, and therefore it can be allocated (or not) to the robotic kitting area ($x_i = 1$ or 0 depending on the previous constraints). Conversely, if $Feas_i = 0$, it indicates that SKU i is not suitable for robotic picking. In this case, the constraint ensures that SKU i is assigned to the collaborative kitting area ($x_i = 0$).

Constraint (3.67) defines the binary type of auxiliary variable b_i.

Together, these assignment constraints determine the allocation of parts between the robotic kitting area and the collaborative kitting area based on the presence of plastic bags, foam interlayers, and the feasibility of robotic picking. By including these types of constraints in the mixed-integer programming operational research model, the resulting model will be able to effectively represent the real-world scenario and provide valuable insights for analysis of its performance.

3.2.2 MIP model for the Sequential Hybrid Kitting (SHK) System

Indexes

The indexes "R" and "C" indicate that a certain parameter or variable refers to the area of robotic or collaborative kitting, respectively, and $i = [1, 2, ..., Z]$ identifies the SKUs within the kitting process (where Z is the total number of SKUs), similarly to what was considered to the model of the AHK System (Subsection 3.2.1).

Parameters

The parameters considered in Subsection 3.2.1 for the AHK System were also considered for the SHK System, except the parameters related to the tugger train and sorting operations. Additionally, some new parameters are considered:

- α - Parameter describing the simultaneous processes execution;
- t_{AGV_kp} - Time required to prepare one kit box into the AGV (s);
- $t_{AGV\_delivery}$ - Average time required to the AGV to perform a delivery from the Warehouse to the BoL;
- $Lim_{kits\_per\_AGV}$ - Number of kit boxes carried in each AGV.

Decision Variables

The decision variables defined for this kitting system were defined analogously to the AHK System in Subsection 3.2.1, without considering the auxiliary decision variables related to the number of trips performed by the AGVs and the tugger train.

Main Decision Variables

- Binary decision variables representing the allocation of SKUs to the robotic or collaborative kitting areas;

$$x_i = \begin{cases} 1, & \text{if SKU } i \text{ is assigned to the robotic kitting} \\ 0, & \text{otherwise} \end{cases} \quad , \forall i = 1 \dots Z \tag{3.68}$$

Auxiliary Decision Variables

- N_{kits} - Integer decision variable representing the number of kits needed to be mounted;

- a - Continuous decision variable representing the maximum cycle time, used due to the linearization;
- $b_i, \quad \forall i = 1 \ldots Z$ - Continuous decision variables to define assignment constraints, used due to the linearization.

Objective Function

The SHK System embraces a distinct operational approach characterized by a seamless flow across the various stages within both the robotic and collaborative kitting areas. This stands in contrast to the AHK System, where operations could operate semi-independently.

The objective function within the SHK System (Equation 3.69) aims to balance the workload between robotic and collaborative kitting areas, considering that the processes are executed sequentially and orderly. In this context, the parameter α is the percentage value for increasing the total cycle time due to the robotic and collaborative cycle time operations not occurring simultaneously. In fact, the robotic kitting process starts, and the collaborative kitting process can only start after the SKUs required for the first kits stored on the robotic side are in the AGV and reach the collaborative kitting area (see Figure 3.8). This refined approach reflects the synchronization of the system and emphasizes the importance of coordinated operations.

$$Minimize\ T_{AGV\_kit\_prep} + Max\left(CT^R, CT^C\right) \cdot (1 + \alpha) + T_{AGV\_to\_BoL} \tag{3.69}$$

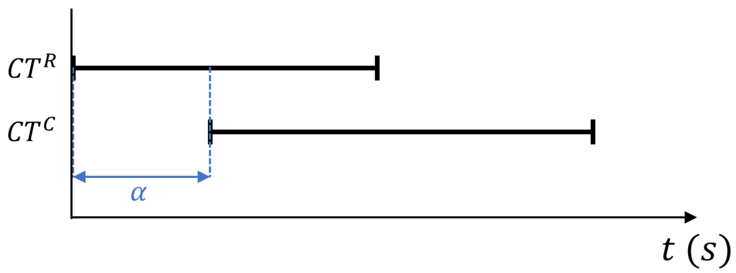


Figure 3.8: Representation of the relation between robotic and collaborative cycle times with parameter α.

Remarkably, the incorporation of AGVs pre-loaded with kit boxes, tailored to the components requirements in the assembly line, fundamentally alters the dynamics of the system. With AGVs now equipped to directly transport the appropriate components to the assembly line, the sorting operation becomes redundant. This consideration streamlines the process, minimizing unnecessary operations and optimizing the flow of materials.

As in the objective function of the previous kitting system (Subsection 3.2.1), the maximum function can be linearized with the introduction of a continuous decision variable, a, and the Constraints (3.71) and (3.72), getting the objective function:

$$Minimize\ T_{AGV\_kit\_prep} + a \cdot (1 + \alpha) + T_{AGV\_to\_BoL} \tag{3.70}$$

Constrains

The formulation of constraints for the SHK System draws upon a similar reasoning employed in devising constraints for the AHK System, presented in Subsection 3.2.1. This congruence in approach ensures that the underlying modeling principles remain consistent across both systems. While adhering to this foundation, some modifications were made, namely the constraints related to the number of AGVs trips. Additionally, constraints associated with the tugger train were also excluded from the formulation, reflecting the evolving nature of AGVs transporting the kits in the SHK System.

Consistency constraints These constraints ensure the model is consistent and error-free, such as verifying variable values against their defined parameters (cf. Subsection 3.2.1).

$$a \geq CT^R \tag{3.71}$$

$$a \geq CT^C \tag{3.72}$$

$$x_i \in \{0, 1\}, \quad \forall i = 1 \ldots Z \tag{3.73}$$

Operational constraints These constraints define system performance and relate to warehouse operations.

Given the similarity between the majority of operations in the SHK System and the previous kitting system, the presentation of these operations is more concise. This is attributed to the foundational framework established in the AHK System, from which the SHK System derives its structure. Consequently, a more succinct depiction of operations is viable, concentrating on the novel features and refinements that the new system introduces. The assumptions considered for the kitting operations in the robotic and collaborative kitting area, presented in Appendices A and B, respectively, are valid for the following presented operations.

AGV Kit Box Preparation Time The AGV kit box preparation time is determined analogously to the one presented for the kit box preparation in the tugger train in the AHK System (Subsection 3.2.1) have now the time to position the kit boxes in the AGVs, t_{AGV_kp}, by a human operator, and it is prepared in the area located before the robotic kitting area. The assumptions for the kit box preparation in the SHK system are presented in Appendix C.

$$T_{AGV\_kit\_prep} = N_{kits} \cdot t_{AGV\_kp} \cdot (1 - Ef_{kit\_prep}) \tag{3.74}$$

Robotic Kitting Cycle Time **(CT^R)**

Image Acquisition Time **(T_{image_acq}):**

Due to the fact that there is no fixed manipulator to sort components to the correct kit box, there is no need for the factor 2 in the Image Acquisition Time (as presented in Subsection 3.2.1).

$$T_{image\_acq} = \sum_{i=1}^{Z} x_i \cdot t_{image} \cdot n_i \cdot f_i \cdot BS \cdot [(1 - Bg) + PE_i] \tag{3.75}$$

AMR Picking Time **(T^R_{pick}):**

As defined in Subsection 3.2.1, the AMR picking time is determined by:

$$T^R_{pick} = \sum_{i=1}^{Z} x_i \cdot T^R_i \cdot n_i \cdot f_i \cdot BS \cdot (1 + PE_i) \tag{3.76}$$

AMR Displacement Time **($T^R_{AGV\_disp}$):**

As formulated in Subsection 3.2.1, the AMR displacement time is determined by:

$$T_{AMR\_disp} = \sum_{i=1}^{Z} x_i \cdot \frac{BW_i + S^R + \left(RL^R - \lfloor \frac{RL^R}{BW_i} \rfloor \cdot BW_i\right)}{N^R_{levels} \cdot Ps^R \cdot AMR \cdot \bar{v}_{AMR}} \tag{3.77}$$

AGV Displacement Time **($T^R_{AGV\_disp}$):**

For the SHK System, the distance traveled by the AGV and the distance traveled by the AMR can be correlated as presented in Figure 3.9.

In this layout, it is intended that the AGV only moves in one direction while receiving components from the AMR in the robotic kitting area, being from the left to the right according to Figure 3.2, in this way it gets closer to the collaborative kitting area. In other words, when the displacement distance of the AMR increases, the displacement distance by the AGV decreases. So, in a typical kitting cycle time, the average distance traveled by the AGV is $\frac{d_{AMR\_total}}{2}$. So, the time needed for the displacement of the AGV can be determined by Equation (3.78).

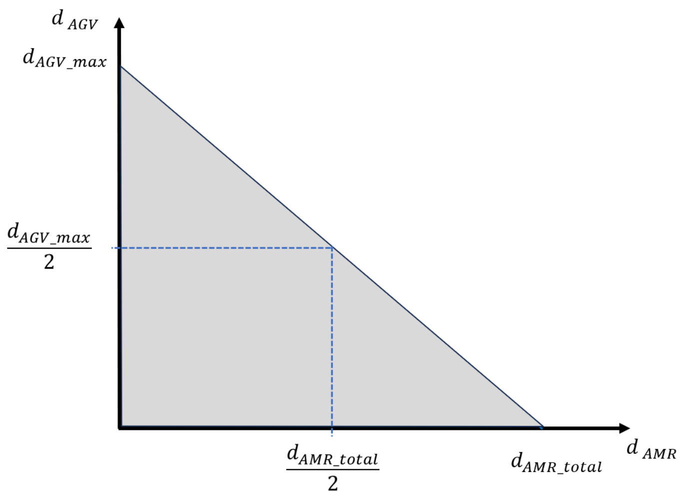


Figure 3.9: Expected of the relation between AMR and AGV traveled distance in the SHK System.

$$T^R_{AGV\_disp} = \frac{1}{\bar{v}_{AGV}} \cdot \frac{d_{AMR\_total}}{2} \tag{3.78}$$

Packaging Removal Time ($T^R_{pack\_rem}$):

As previously defined in Subsection 3.2.1, the packaging removal time is determined by:

$$T^R_{pack\_rem} = \sum_{i=1}^{Z} x_i \cdot \frac{n_i \cdot f_i \cdot BS}{P_i} \cdot \left[IL_i \cdot t^R_{IL} \cdot (1 + PE_{interlayer}) + D_i \cdot t^R_D \cdot (1 + PE_{divider}) \right] \tag{3.79}$$

Empty Bin Removal Time ($T^R_{bin\_rem}$):

As previously described in Subsection 3.2.1, the empty bin removal time is determined by:

$$T^R_{bin\_rem} = \sum_{i=1}^{Z} x_i \cdot t^R_{bin} \cdot \frac{n_i \cdot f_i \cdot BS}{P_i} \cdot (1 + PE_{bin}) \tag{3.80}$$

Gripper Change Time ($T_{gripper}$):

As defined in Subsection 3.2.1, the empty bin removal time, without considering the gripper change for the fixed manipulator in the SHK System, is determined by:

$$
\begin{aligned}
T_{gripper} = (1 + Cal) \sum_{i=1}^{Z} x_i \cdot f_i \cdot BS \left[t_{gripper\_parts} \cdot AR_{parts} + \right. \\
\left. + \frac{n_i}{P_i} \left((IL_i + D_i) \cdot t_{griper\_pack} \cdot AR_{pack} + t_{gripper\_bin} \cdot AR_{bins} \right) \right]
\end{aligned} \tag{3.81}
$$

The cycle time for the robotic kitting area CT^R, in the SHK System, to prepare BS EPs is given by:

$$
\begin{aligned}
CT^R = T_{image\_acq} + T^R_{pick} + T_{AMR\_disp} + T^R_{AGV\_disp} + \\
+ T^R_{pack\_rem} + T^R_{bin\_rem} + T_{gripper}
\end{aligned} \tag{3.82}
$$

Collaborative Kitting Cycle Time (CT^C)

Pick-to-Light System Identification Time (T_{p2l}):

As presented in Subsection 3.2.1, the Pick-to-Light system identification time is given by:

$$
T_{p2l} = t_{p2l} \cdot (1 + EC_{com}) + \sum_{i=1}^{Z} (1 - x_i) \cdot t_{obs} \cdot (1 + EC_{obs} + EC_{detect}) \tag{3.83}
$$

Operator Picking Time (T_{OP_disp}):

As defined in Subsection 3.2.1, the operator picking time is given by:

$$
T^C_{pick} = \sum_{i=1}^{Z} (1 - x_i) \cdot t^C_i \cdot \frac{n_i \cdot f_i \cdot BS}{sim_i} \tag{3.84}
$$

Operator Displacement Time (T_{OP_disp}):

As presented in Subsection 3.2.1, the operator displacement time is given by:

$$
T_{OP\_disp} = \sum_{i=1}^{Z} (1 - x_i) \cdot \frac{BW_i + S^C + \left(RL^C - \lfloor \frac{RL^C}{BW_i} \rfloor \cdot BW_i \right)}{N^C_{levels} \cdot Ps^C \cdot OP \cdot \bar{v}_{OP}} \tag{3.85}
$$

AGV Displacement Time ($T^C_{AGV\_disp}$):

In the collaborative kitting area, the movement of the AGV follows a unidirectional path, mirroring the pattern observed in the trajectory of the AGV within the robotic kitting domain. In this context, the AGV starts its motion from the collaborative kitting section adjacent to the robotic kitting area, progressively advancing toward the designated exit zone. This exit point serves as the gateway to a designated route facilitating the transportation of completed kits to the assembly line. Notably, as the cumulative distance traversed by the operator increases, the corresponding distance to be covered by the AGV diminishes. Consequently, within a standard kitting cycle duration, the displacement distance of the AGV is mathematically approximated as half of the total traveled distance by the operator, i.e., $\frac{d_{OP\_total}}{2}$. Consequently, the duration required for AGV displacement is determined by:

$$T^{C}_{AGV\_disp} = \frac{1}{\bar{v}_{AGV}} \cdot \frac{d_{OP\_total}}{2} \tag{3.86}$$

Packaging Removal Time $\left(T^{C}_{pack\_rem}\right)$**:**

As presented in Subsection 3.2.1, the packaging removal time is given by:

$$T^{C}_{pack\_rem} = \sum_{i=1}^{Z} (1 - x_i) \cdot \frac{n_i \cdot f_i \cdot BS}{P_i \cdot sim_{pack}} \cdot \left[IL_i \cdot t^{C}_{IL} + D_i \cdot t^{C}_{D} + Fo_i \cdot t_F + PB_i \cdot t_{PB} \right] \tag{3.87}$$

Empty Bin Removal Time $\left(T_{gripper}\right)$**:**

As presented in Subsection 3.2.1, the empty bin removal time is given by:

$$T^{C}_{bin\_rem} = \sum_{i=1}^{Z} (1 - x_i) \cdot t^{C}_{bin} \cdot \frac{n_i \cdot f_i \cdot BS}{P_i} \tag{3.88}$$

The cycle time for the collaborative kitting area CT^C, in the SHK System, to prepare BS EPs is given by:

$$\begin{aligned} CT^{C} = T_{p2l} + T^{C}_{pick} + T_{OP\_disp} + T^{C}_{AGV\_disp} + \\ + T^{C}_{pack\_rem} + T^{C}_{bin\_rem} \end{aligned} \tag{3.89}$$

AGVs to the BoL Time $\left(T_{AGV\_to\_BoL}\right)$**:**

Once the kits have been fully assembled within the AGVs and have reached the designated exit zone, the AGVs proceed to travel collectively along a pre-defined route toward a specific zone of demand for the kits in the BoL. Notably, due to the independent nature of each AGV, upon reaching its individual destination area, an AGV can disengage from the convoy without necessitating a stop for the entire AGV train. As a result, the temporal impact of this particular operation on the overall cycle time is primarily contingent upon the travel duration of the final AGV taking a complete kit. In this way, this impact is described by a linear expression, as it corresponds directly to the duration of the journey undertaken by the last AGV with the complete kit. The assumptions considered for this operation are presented in Appendix C.

$$T_{AGV\_to\_BoL} = t_{AGV\_delivery} \tag{3.90}$$

For analysis purposes, the total time taken by the AGV to deliver all kits is given by the time needed for one AGV trip, $t_{AGV\_delivery}$, for all the $\frac{N\_kits}{Lim_{kits\_per\_AGV}}$ trips needed to be performed.

$$T_{AGV\_to\_BoL\_total} = t_{AGV\_delivery} \cdot \frac{N\_kits}{Lim_{kits\_per\_AGV}} \tag{3.91}$$

Constraints (3.92) and (3.93) define the numbers of kit boxes mounted based on the weight and volume capacities of the kit boxes.

$$N_{kits} \geq \frac{\sum_{i=1}^{Z} n_i \cdot f_i \cdot BS \cdot M_i}{M_{kit}} \tag{3.92}$$

$$N_{kits} \geq \frac{\sum_{i=1}^{Z} n_i \cdot f_i \cdot BS \cdot Vol_i}{Vol_{kit}} \tag{3.93}$$

Layout constraints This constraint defines the physical limitations of the warehouse, similarly to what was presented in Subsection 3.2.1.

$$\sum_{i=1}^{i=C} \left[x_i \cdot \frac{\left(AW^R + F^R \cdot RD^R\right) \cdot \left(BW_i + S^R\right)}{N^R_{levels}} + \right. \\ \left. + (1 - x_i) \cdot \frac{\left(AW^C + F^C \cdot RD^C\right) \cdot \left(BW_i + S^C\right)}{N^C_{levels}} \right] \leq A \tag{3.94}$$

Assignment constraints These constraints define the limitation in allocating certain components to the robotic kitting area, similarly to what was defined in Subsection 3.2.1.

$$PB_i \leq L \cdot b_i, \quad \forall i = 1 \ldots Z \tag{3.95}$$

$$Fo_i \leq L \cdot b_i, \quad \forall i = 1 \ldots Z \tag{3.96}$$

$$Feas_i \geq 1 - b_i, \quad \forall i = 1 \ldots Z \tag{3.97}$$

$$x_i \leq 1 - b_i, \quad \forall i = 1 \ldots Z \tag{3.98}$$

$$b_i \in \{0, 1\}, \quad \forall i = 1 \ldots Z \tag{3.99}$$

Chapter 4

Results and Discussion

In this chapter, the Mixed Integer Programming (MIP) models presented in the preceding chapter will be experimentally tested to validate the outcomes rigorously. This chapter thoroughly examines the resultant outcomes through a comprehensive numerical analysis of diverse scenarios, fostering insightful discussions on the implications and nuances of the acquired results.

4.1 Input data

The data inputs for the developed MIP models were obtained through a variety of sources, including:

1. **Experts from the automotive company:** A close contact with experts within the automotive company to define the layouts and specific parameters related to SKU characteristics and warehouse dimensions for the MIP models and to ensure that they were aligned with the objectives of the project.

2. **Contacts with technological solutions providers:** Several experts in the field of robotics, warehouse automation, operational research, and hardware communication networks, partners of the automotive company from which this dissertation originated, to gather information to define and realistically estimate based on laboratory tests AMR and AGV parameters related to performing the picking operations, for human operators related parameters and also for the pick to light system.

3. **Information obtained from the scientific literature:** Based on the scientific literature on warehouse logistics and automation, information was gathered on the performance of different technological solutions. This information was used to validate the parameters of the MIP models and ensure they were realistic.

4. **Datasheets from sensors and devices:** The obtained datasheets of several sensors, AGVs, AMRs, and devices that could be used in warehouse automation were considered. This information was used to define the ac-

curacy and reliability of the AMR on picking performance, typical AGVs maximum weight and volume capacity, AGV, AMR, and operator speeds and standards on kit boxes volume and weight limits, which was then used to feed the MIP models.

A sample of 165 SKUs was considered, all consumed by End Products (EPs) during a cycle time, with different characteristics, demand, and packaging items, where 126 SKUs (76.36%) are feasible to have robotic picking. Due to the extensive list of parameters needed for the model, an Appendix E is presented to gather the data considered in this analysis.

In order to assess the practical applicability of the models developed in this dissertation, a sensitivity analysis for different parameters for both hybrid kitting systems was developed to understand their impact on the systems, and a set of scenarios was meticulously constructed aimed at evaluating the responsiveness of the models and reliability in real-world contexts, ensuring its capacity to deliver timely solutions. For conducting data visualization and analysis, software tools such as *Microsoft Excel* and *MATLAB* were used.

Following the methodology presented earlier in Chapter 3, it is noteworthy that the problem-solving process for all simulations performed was completed in a few seconds. This computational efficiency was achieved utilizing the following hardware and software configurations:

- *Asus* laptop equipped with a 2.6 GHz Intel(R) Core(TM) i7 CPU, 32 GB of RAM, a 64-bit operating system and a *NVIDIA GeForce GTX* 960M graphics card;
- *PyCharm Professional 2023.2* served as the Integrated Development Environment (IDE) for the Python-based code (Python Version: 3.10);
- *IBM LOG CPLEX Academic Edition* Application Programming Interface (API), integrated seamlessly with PyCharm (CPLEX Version: 22.1.1.0);

4.2 Sensitivity Analysis for the Asynchronous Hybrid Kitting System

4.2.1 Optimal Assignment

The optimal assignment for the Asynchronous Hybrid Kitting System, considering one AMR (with picking errors of 5%) and one operator picking components, having 358 variables (330 binary variables, 4 integer variables and 24 continuous variables) and 693 constraints, was obtained in 1.155 seconds, where the total cycle time, since the preparation of the kits until delivering them to the Border of Line (BoL) is 2049.181s, for all the 199 kits mounted.

Table 4.1: Results obtained for the Asynchronous Hybrid Kitting System in the optimal assignment.

Area	Variable (Units)	Result
Robotic	CT^R (s)	1980.976
	$N^R_{AGV\_trips}$	9
	$\# SKUs$	46 (27.88%)
Collaborative	CT^C (s)	1981.181
	$N^C_{AGV\_trips}$	4
	$\# SKUs$	119 (72.12%)
Tugger Train	T_{tugger} (s)	460
	$N_{tugger\_train\_trips}$	13
	T_{tugger_total} (s)	2073.500
	CT_{Total} (s)	2441.181
	N_{kits}	199
	Vol_{buffer} (m^3)	10.0

Analyzing the results presented in Table 4.1, it can be seen that the balance between the robotic kitting area operations and the collaborative kitting area operations is achieved since the proximity in the values of CT^R and CT^C (1980.976 seconds and 1981.181 seconds, respectively). It can also be observed that more than two-thirds of all components are allocated to the collaborative kitting area, having 72.12% of SKUs in the collaborative and only 27.88% in the robotic kitting areas. After analyzing the characteristics of the SKU allocated for each area, it is seen that the majority of the components in the collaborative area have smaller dimensions, contrary to the robotic kitting area, in which bigger components were allocated. The SKUs of smaller dimensions normally have higher quantities needed, and taking advantage of the human operator picking multiple components simultaneously, this attribution is coherent with the findings of Boudella et al. (2018).

It can be also seen that AGV performs more than double the number of trips in the robotic kitting area, which is coherent with the previously explained, where bigger and heavier pieces are transported, so the capacity of AGV is more quickly achieved, needing to perform more trips. Relatively to the tugger train, the time required to deliver the last kits to the BoL was 460 seconds, representing 18.8% of the total cycle time, found to be consistent with Boysen et al. (2015), accounting for between 10% and 20% of the cycle time.

The results presented in Figure 4.1 depict the duration of each operation in the kitting areas. According to Figure 4.1a, the most time-consuming task for the robotic cycle time is picking all the components, which constitutes 37% of the entire cycle time. It is expected that this task would take a considerable amount of time since the AMR takes 4 to 7 seconds to pick a single SKU. The next most impactful operation is the sorting time, where the fixed manipulator picks SKUs from the AGV and moves them to the final kit box. Together, these two operations account for nearly 60% of the robotic kitting time. The third most impactful operation is image acquisition, which occurs twice for both the AMR and the fixed manipulator.

This task takes a considerable amount of time to process the positions of SKUs in the bins to define a correct patch for picking them correctly. The AMR displacement and AGV displacement are tasks with less impact on the cycle time, accounting for less than 4% of the robotic cycle time, which represents a significant improvement compared to the more than 10% in Boudella et al. (2018). Since the majority of SKUs had smaller component consumption than those components present in full bins, removing a few empty bins was justified, and, consequently, a small empty bins removal time.

For the collaborative kitting cycle time, illustrated in the Pareto chart in Figure 4.1b, it is evident that the kit box preparation stage consumes the most significant portion of the cycle time. This outcome aligns with expectations, given that this phase is responsible for preparing all the kit boxes destined for the BoL. Notably, it constitutes 26.8% of the total collaborative kitting cycle time. Following closely are the component picking and sorting operations, accounting for 23.6% and 21.3% of the cycle time, respectively. In this context, it was considered that human operators can take between 2 to 5 seconds to pick an SKU, a shorter time compared to the AMR. Moreover, operators have the advantage of being able to pick between 1 to 6 SKUs simultaneously, providing a considerable advantage compared to the AMR, which can handle only one component at a time. Consequently, the picking time in the collaborative area is substantially lower than in the robotic area, despite having a higher number of SKUs allocated. The operation of packaging removal contributes 12.9% to the cycle time, while the pick-to-light system, with a similar impact as the bin removal operation, accounts for 6.3% and 5.8% of the cycle time, respectively.

Comparatively, the travel times for both the operator and the AGVs have the least impact on the collaborative kitting cycle time, mirroring the observations in the robotic kitting cycle. These travel times collectively represent less than 4% of the collaborative cycle time, representing a notable improvement in operational efficiency in transportation-related processes.

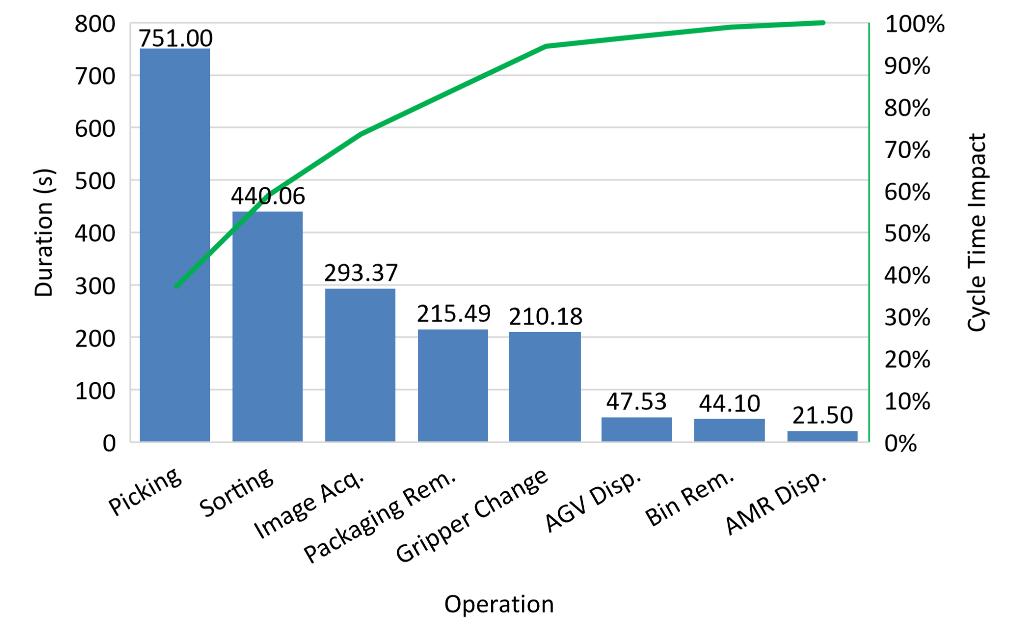
In this way, the approach taken seems to be effective in reducing traveling and transportation times required in the warehouse, which was the objective of this hybrid kitting system.

4.2.2 Impact from the Batch Size

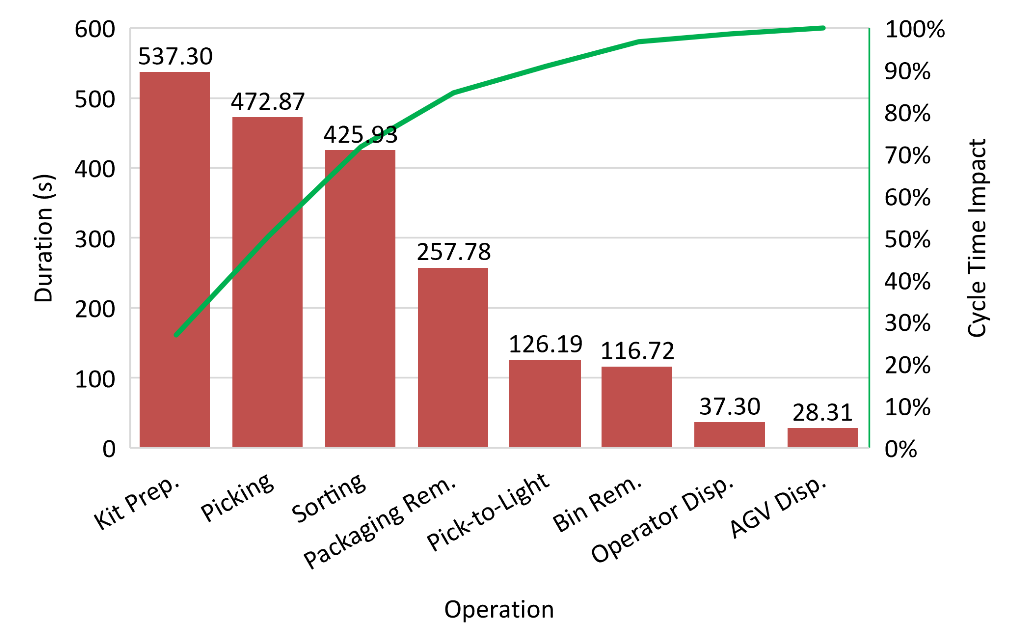
The batch size refers to the quantity of EPs produced simultaneously during the reference cycle time. With more SKUs and kits to prepare when BS increases, it is expected that the duration of most operations in both kitting areas should increase.

As shown in Figure 4.2, the expected increases in the cycle times for both the robotic and collaborative kitting areas were obtained, and these increases are balanced between the two kitting areas, leading to a consequent increase in the total cycle time.

From Table 4.2, it can be observed that the number of AGV trips increases more



(a) Robotic cycle time operations.



(b) Collaborative cycle time operations.

Figure 4.1: Characterization of Asynchronous Hybrid Kitting System cycle time in the optimal assignment.

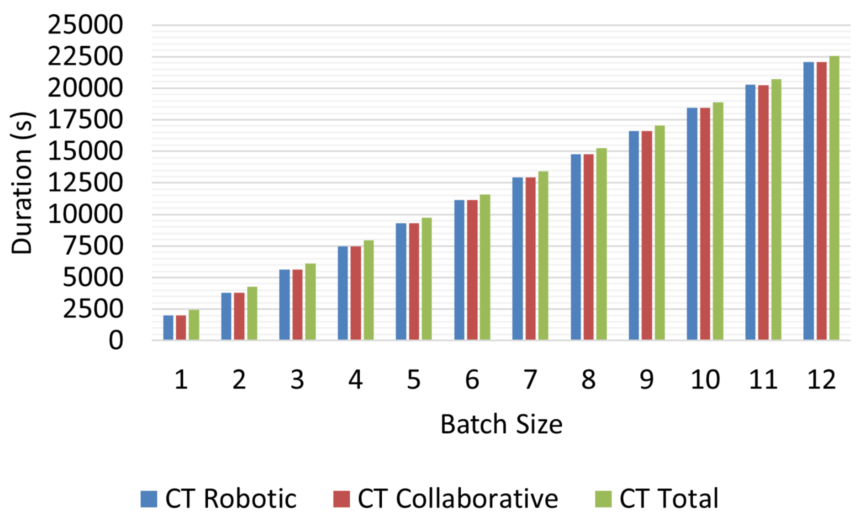


Figure 4.2: Robotic, collaborative and total cycle times according to the batch size for the Asynchronous Hybrid Kitting System.

rapidly for the robotic kitting area than for the collaborative kitting area. This difference is due to the characteristics of the larger-sized SKUs in the robotic area compared to those allocated to the collaborative area, as explained in the previous section. As the batch size increases, there is a redistribution of SKUs, favoring the collaborative side. This is expected due to the faster speed of picking and sorting operations on the collaborative side compared to the robotic.

Table 4.2: Impact from the batch size on cycle times and SKU allocation for the Asynchronous Hybrid Kitting System.

BS	**CT_{total} (s)**	**#SKUs Robotic**	**#SKUs Collab.**	**$N^{R}_{AGV\_trips}$**	**$N^{C}_{AGV\_trips}$**
1	2441.181	46	119	9	4
2	4274.513	38	127	17	7
3	6102.993	34	131	24	11
4	7931.407	28	137	32	14
5	9758.794	30	135	40	18
6	11585.406	30	135	48	21
7	13409.952	29	136	55	25
8	15235.483	29	136	63	28
9	17062.7216	28	137	71	32
10	18888.3844	27	138	79	35
11	20717.1125	29	136	87	38
12	22541.5606	28	137	94	42

In Figure 4.3, the variation in cycle time according to the batch size becomes more evident. Increasing the batch size from 1 to 2 results in approximately a 75% increase in the total cycle time, while changing it from 2 to 3 results in a 43% increase. This percentage variation in cycle time tends to stabilize for larger batch sizes. For instance, when increasing from 7 to 8 and for batch sizes higher than 8, the cycle time tends to increase by approximately 10% for each unit increase in BS.

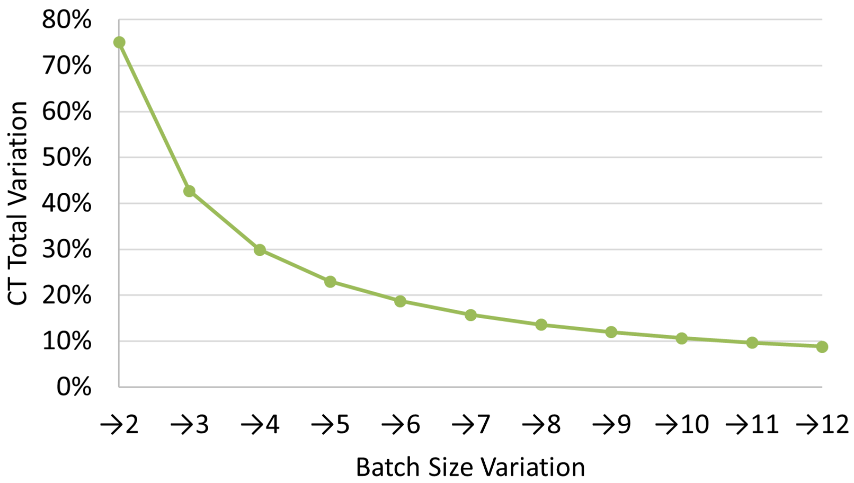


Figure 4.3: Total cycle time percentage variation according to the batch size for the Asynchronous Hybrid Kitting System.

4.2.3 Impact from the Picking Errors

Many authors state that studies of picking errors in kitting systems should be carried out although there are few in the literature (Caputo et al. (2021), Boudella et al. (2018)).

Picking errors manifest themselves across various operations of the Robotic Kitting Area, including picking SKUs from their respective bins (PE_i), picking empty bins from the shelves (PE_{bin}), picking SKUs during the sorting process (PE_{sort}), handling interlayer sheets within the bins ($PE_{interlayer}$), and picking bin dividers ($PE_{divider}$). These five types of picking errors were analyzed, ranging from 1% to 50% error rates, covering a spectrum from minimal to extreme error conditions. This assessment aimed to understand the impact of these error rates on the cycle times of kitting operations.

Examining the results presented in Table 4.3, it is evident that a balance between robotic and collaborative cycle times was consistently kept. As anticipated, a higher rate of picking errors corresponds to longer cycle times. For instance, the transition from a 1% error rate to 10% results in an increase of approximately 31 seconds in the total cycle time. This increment escalates to about 140 seconds when the error rate is elevated to 50%.

The picking error parameters do not appear to be a critical point for the kitting system, as there is no substantial increase in the total cycle time. This is primarily due to the dynamic redistribution of SKUs across the kitting areas, favoring the collaborative side over the robotic side. This redistribution compensates for the penalties incurred by picking errors on the AMR and fixed manipulator operations, as evidenced in Figure 4.4.

Concerning the Robotic Kitting Area (Figure 4.5a), it is noteworthy that image acquisition is the most affected operation by increasing picking errors. When a picking attempt fails, both the AMR and the fixed manipulator must repeat the

Table 4.3: Impact from picking errors on cycle times and SKU allocation for the Asynchronous Hybrid Kitting System.

PE	CT^R (s)	CT^C (s)	CT_{total} (s)	#SKUs Robotic	#SKUs Collab.
1%	1967.122	1966.886	2427.122	48	117
2%	1969.577	1970.665	2430.665	49	116
5%	1980.976	1981.181	2441.181	46	119
10%	1997.566	1998.431	2458.431	44	121
20%	2029.036	2029.477	2489.477	44	121
30%	2057.207	2057.382	2517.382	41	124
40%	2080.742	2082.609	2542.609	37	128
50%	2106.401	2106.378	2566.401	35	130

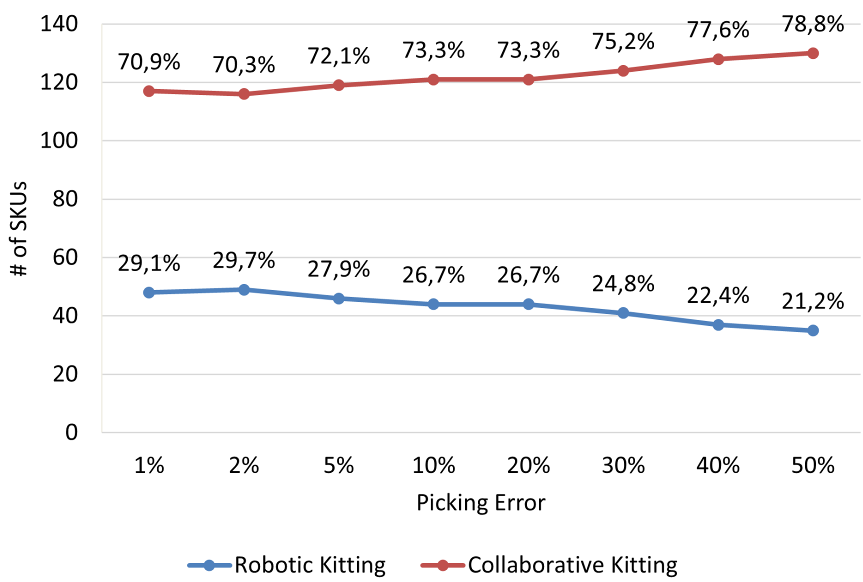


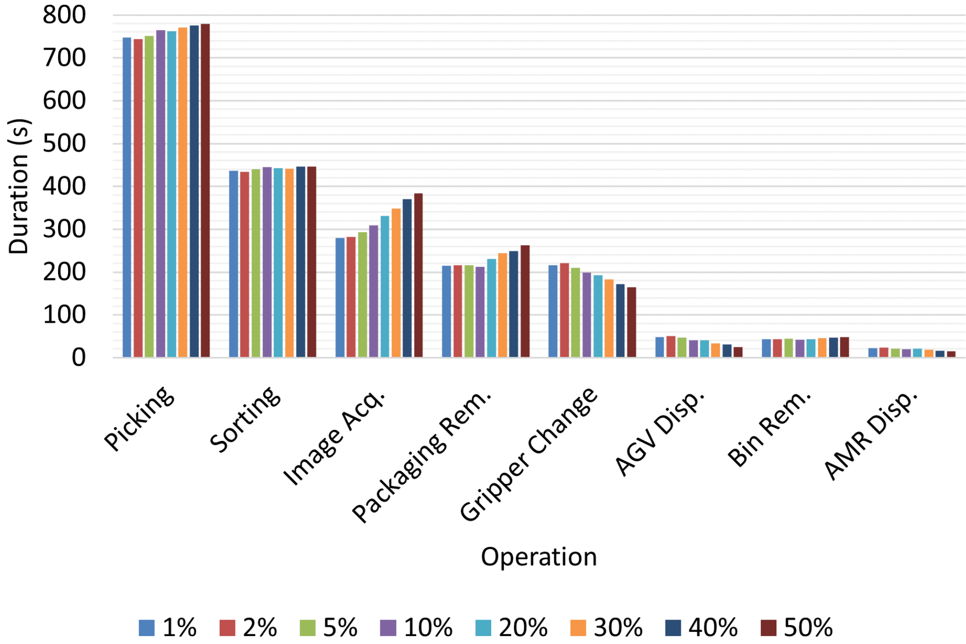
Figure 4.4: SKU allocation according to the robotic picking errors for the Asynchronous Hybrid Kitting System.

image processing to identify the new SKU arrangement before initiating another picking attempt. Consequently, the picking and sorting operations, along with the packaging removal, contribute to the increased cycle time. Contrariwise, operations such as AGV displacement, empty bin removal, and AGV displacement experience reduced cycle times due to the reduced allocation of SKUs in this area.

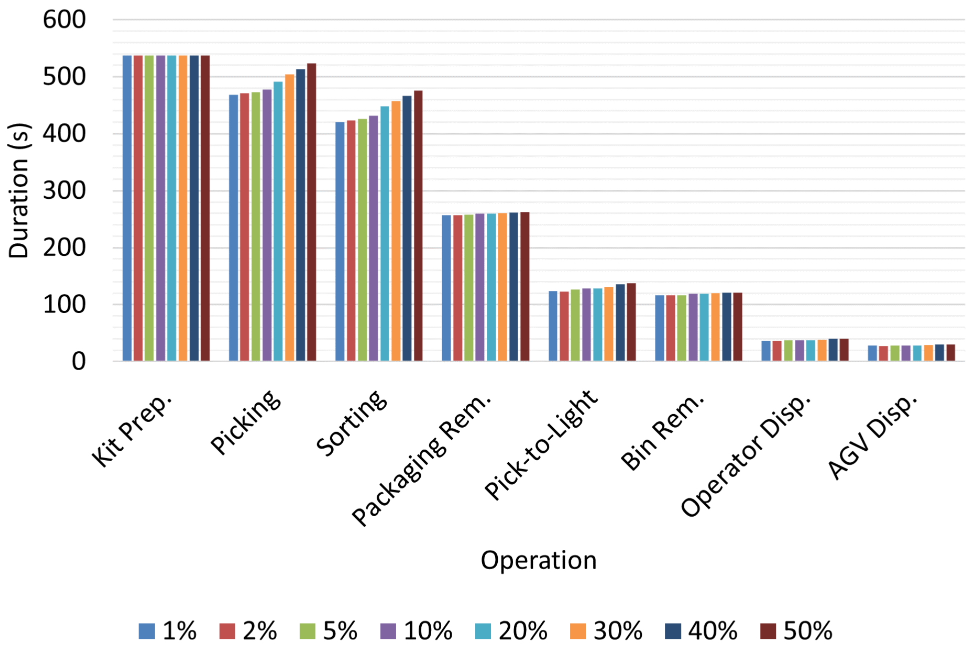
In the Collaborative Kitting Area (Figure 4.5b), a more substantial increase in cycle times is observed for the picking and sorting operations, while the impact on the pick-to-light system operation is comparatively lower. This effect is attributed to the higher allocation of SKUs in the collaborative area.

4.2.4 Impact from Simultaneous Picking

An efficiency-enhancing factor for collaborative picking activities is the ability of human operators to pick multiple SKUs simultaneously, reducing the number of



(a) Robotic cycle time.



(b) Collaborative cycle time.

Figure 4.5: Robotic and collaborative cycle times according to picking errors by the AMR(s) and fixed manipulator for the Asynchronous Hybrid Kitting System.

required movements and, consequently, the time needed for picking and sorting operations.

According to the data considered for numerical analysis, the number of SKUs that an operator can pick simultaneously, denoted as sim_i, can range from 1 to 6, while the number of packaging items was considered to be 2 items, one in each hand of the operator. These values were changed from -25%[1] to an increase of 100%.

From Table 4.4, it can be observed from column "**Var CT**" that if sim_i is penalized by 25%, there is an increase in both robotic and collaborative cycle times, resulting in a 17.8% increase in the total cycle time. Conversely, an increase in the number of items that an operator can pick simultaneously leads to significant improvements in cycle time, along with the allocation of more SKUs to the collaborative side. It is evident that this parameter has a considerable impact on the overall efficiency of the system.

Table 4.4: Impact from simultaneous parts picked by the operator on cycle times and SKU allocation for the Asynchronous Hybrid Kitting System.

sim	CT^R (s)	CT^C (s)	CT_{total} (s)	Var CT	#SKUs Rob.	#SKUs Collab.
-25%	2415.513	2416.417	2876.417	17.8%	55	110
0%	1980.976	1981.181	2441.181	-	46	119
25%	1829.693	1830.343	2290.343	-6.2%	46	119
50%	1651.216	1651.156	2111.216	-13.5%	42	123
75%	1572.371	1572.358	2032.371	-16.7%	46	119
100%	1470.702	1472.428	1932.428	-20.8%	45	120

Upon analyzing the time required to perform various tasks at the kitting, it can be observed, from Figure 4.6b, a substantial increase in the duration of picking and sorting operations when sim_i decreases by 25%, as well as the packaging removal operation, which doubles in duration when reducing the number of items removed from 2 to 1. Conversely, with an increase in sim, we see a significant reduction in the duration of these operations.

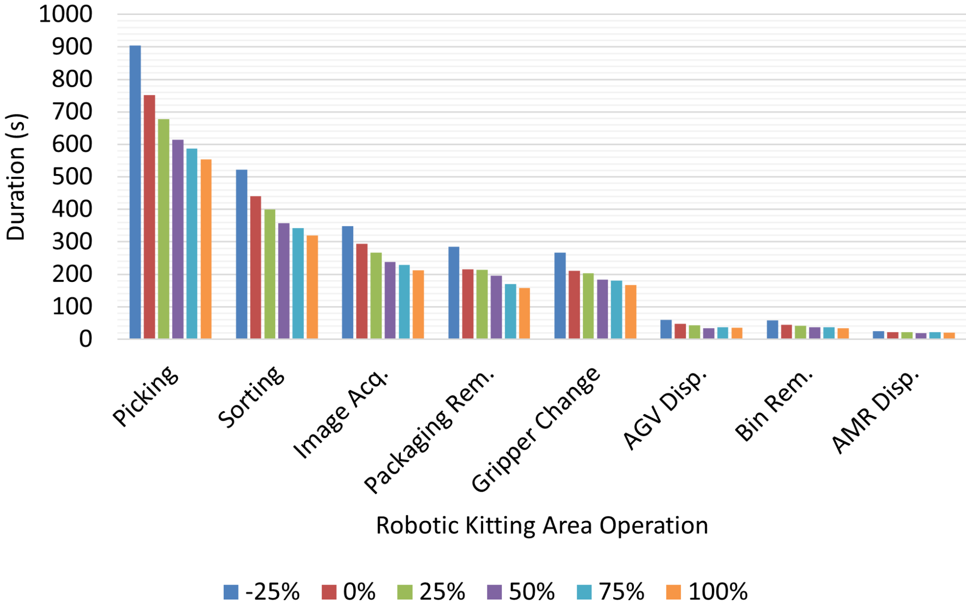
In the cycle time of the robotic area (Figure 4.6a), we observe a reduction in the duration of all operations, which is due to the reallocation of more components to the collaborative side.

4.2.5 Impact from the Number of AMRs and Operators

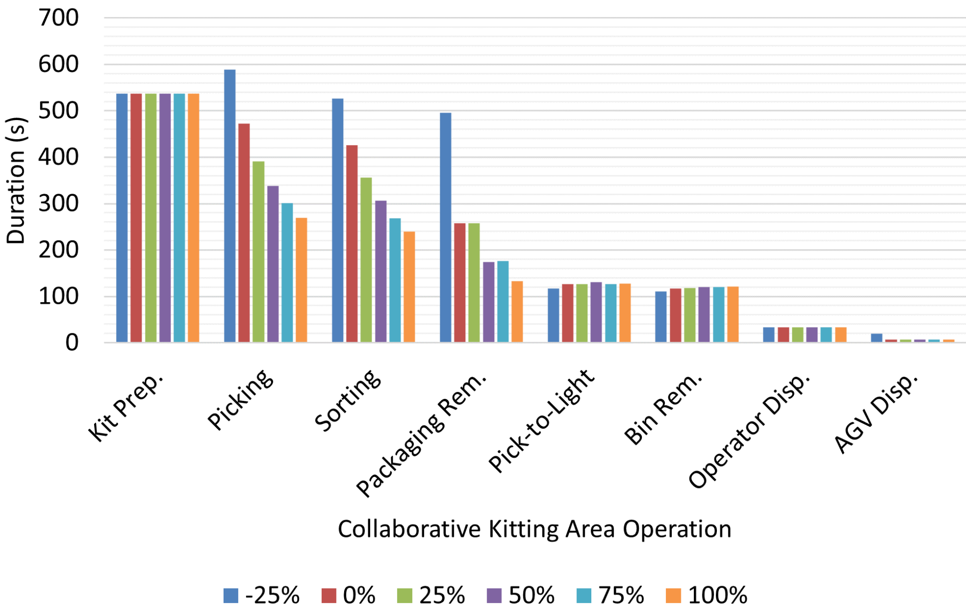
To explicitly demonstrate the impact of the number of AMRs and human operators in the system, several simulations were conducted to test different combinations of values for the number of AMRs and the number of human operators present in the robotic and collaborative kitting areas, respectively.

Observing the three-dimensional graph in Figure 4.7, it can be concluded that

[1]For SKUs with $sim_i = 1$ in the optimal assignment, it was programmed sim_i also equal to 1 in the simulations with a variation of -25% for simultaneous picking.



(a) Robotic cycle time.



(b) Collaborative cycle time.

Figure 4.6: Robotic and collaborative cycle times according to simultaneous picked parts by the operator for the Asynchronous Hybrid Kitting System.

for a given number of operators, as the number of AMRs increases, the cycle time decreases slightly. However, for a given number of AMRs in the system, an increase in the number of operators results in a more significant improvement in cycle time. This graph provides valuable insights to the kitting area manager, indicating that if it is not possible to allocate a new AMR and operator to the kitting area to reduce cycle time because of the financial responsibility this would place on the company, it should be opted for allocating an additional operator, as it leads to a greater reduction in cycle time.

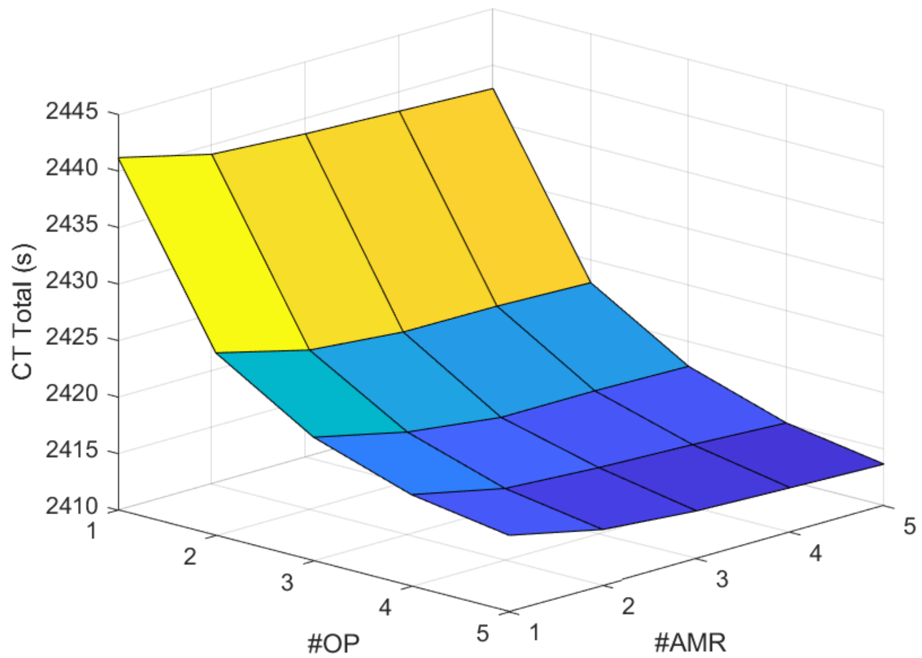


Figure 4.7: Total cycle time according to the number of AMR and Operators for the Asynchronous Hybrid Kitting System.

4.2.6 Impact from Collaboration in the Sorting Zone

In the sorting zone, the operator and the fixed manipulator must work in synergy to place all the required SKUs into the correct kits positioned on the tugger train. When the operator places an SKU into a specific kit box, and the manipulator also intends to place a component into the same kit, the manipulator has to wait for the operator to complete the operation, guaranteeing the safety in the operations. Consequently, the parameter Col influences an increase in the time taken for the sorting operation in the robotic area.

By analyzing the parameter Col, varying from 1% to 50%, being related to the time that the fixed manipulator pauses its operation, it is observed from Table 4.5 that there is an increase in the cycle time for both kitting areas and, consequently, the total cycle time. As expected, there is a redistribution of SKUs, but the variation in cycle time remains smaller than the one observed in the picking errors. In this case, a transition from 1% to 50% only results in an increase of approximately 35 seconds to the total cycle time, suggesting that it does not significantly impact the system.

Table 4.5: Impact from collaboration in the sorting zone on cycle times and SKU allocation for the Asynchronous Hybrid Kitting System.

Col	$\mathbf{CT^R}$ **(s)**	$\mathbf{CT^C}$ **(s)**	$\mathbf{CT_{total}}$ **(s)**	**#SKUs Robotic**	**#SKUs Collab.**
1%	1977.680	1978.241	2438.241	47	118
2%	1978.867	1978.853	2438.867	47	118
5%	1980.976	1981.181	2441.181	46	119
10%	1984.261	1984.853	2444.853	46	119
20%	1991.645	1992.172	2452.172	43	122
30%	1997.715	1999.396	2459.396	44	121
40%	2006.404	2006.430	2466.430	41	124
50%	2012.224	2012.832	2472.832	38	127

Figure 4.8a explicitly presents the increase in the sorting operation time for the robotic area and a generalized small reduction in other operations due to the redistribution of SKUs. This leads to a slight increase in the duration of the operations within the collaborative kitting area (except for the kit box preparation operation, which remains constant as it does not vary with changes in SKU allocation), as shown in Figure 4.8b.

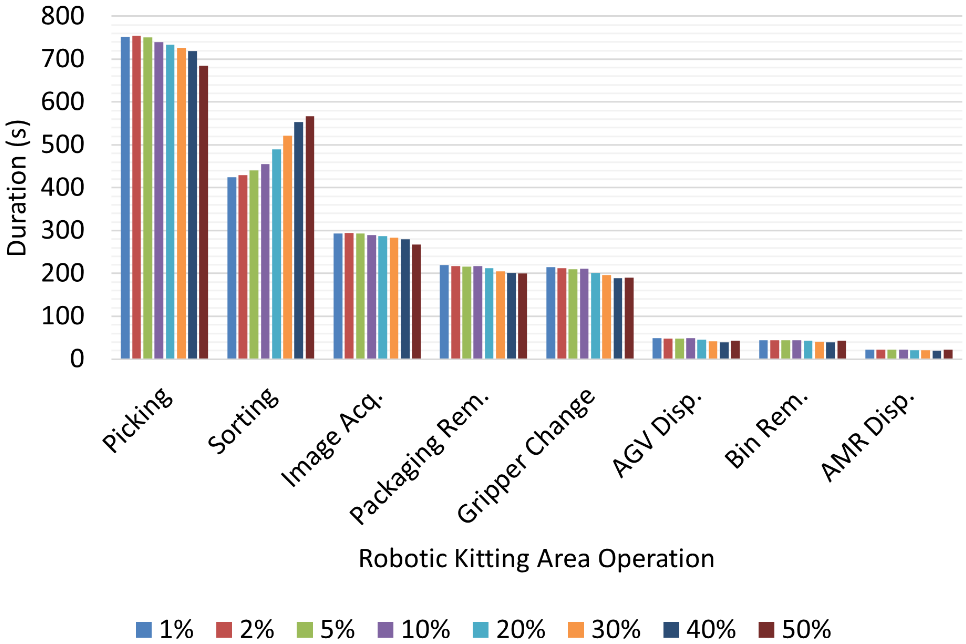
4.3 Sensitivity Analysis for the Sequential Hybrid Kitting System

4.3.1 Optimal Assignment

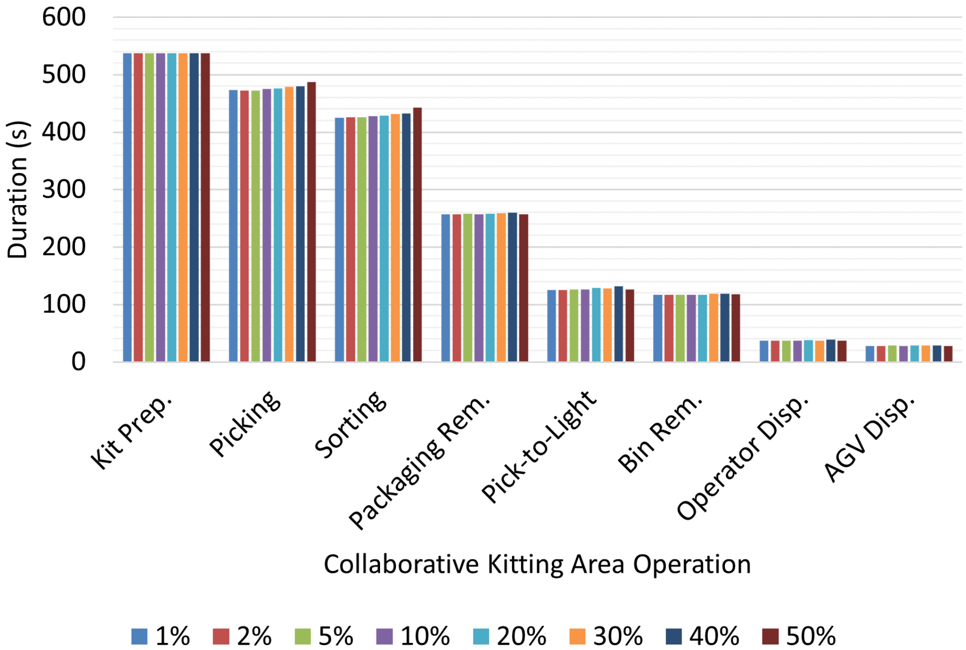
Analogously to the previous system, the optimal assignment was obtained for the Sequential Hybrid Kitting System, being defined 352 decision variables (330 binary, 1 integer, and 21 continuous variables) and 685 constraints. The results were obtained in 1.208 seconds.

From the cycle times in the robotic and collaborative areas, as shown in Table 4.6, it can be noticed a balance between these times due to their closeness. There is a higher allocation of SKUs in the collaborative area compared to the Asynchronous Hybrid Kitting System, which was expected because, in this system, the preparation of kits is not incorporated into the collaborative kitting area, occurring before the AGVs enter the robotic kitting area. Therefore, the collaborative kitting area can accommodate more SKUs, reducing the cycle time for this area and, consequently, the overall cycle time.

From Figure 4.9, it can be noticed that the picking operation has the most significant impact for both kitting areas, accounting for 52.26% and 47.30% of the cycle times in the robotic and collaborative areas, respectively. This highlights the importance of optimizing and improving the process and equipment used for component picking. Similarly, the packaging removal operation ranks second as the most impactful operation in both the robotic and collaborative cycle times, accounting for 16.88% and 24.10%, respectively.



(a) Robotic cycle time.



(b) Collaborative cycle time.

Figure 4.8: Robotic and collaborative cycle times according to the collaboration parameter for the Asynchronous Hybrid Kitting System.

Table 4.6: Results obtained for the Sequential Hybrid Kitting System in the optimal assignment.

Area	Variable (Units)	Result
Robotic	CT^R (s)	1087.647
	# Components	36 (21.82%)
Collaborative	CT^C (s)	1088.598
	# Components	129 (78,18%)
Kit Preparation	$T_{AGV\_kit\_prep}$ (s)	358.200
Delivery to BoL	$T_{AGV\_to\_BoL}$ (s)	300
	$T_{AGV\_to\_BoL\_total}$ (s)	2985
	CT_{Total} (s)	2073.3778
	N_{kits}	199

It is noticeable that the model provides solutions where the movements of the AMR, human operator, and AGVs are not very significant, avoiding unnecessary travel times in the kitting process which leads to minimal impact on the total cycle time. This is a desired outcome in the approach considered for the kitting systems, outperforming the results of Boudella et al. (2018), where the picker (robot or operator) has to travel from the starting point to the location of the SKU to be picked and, after picking the component, it has to travel back to the starting point.

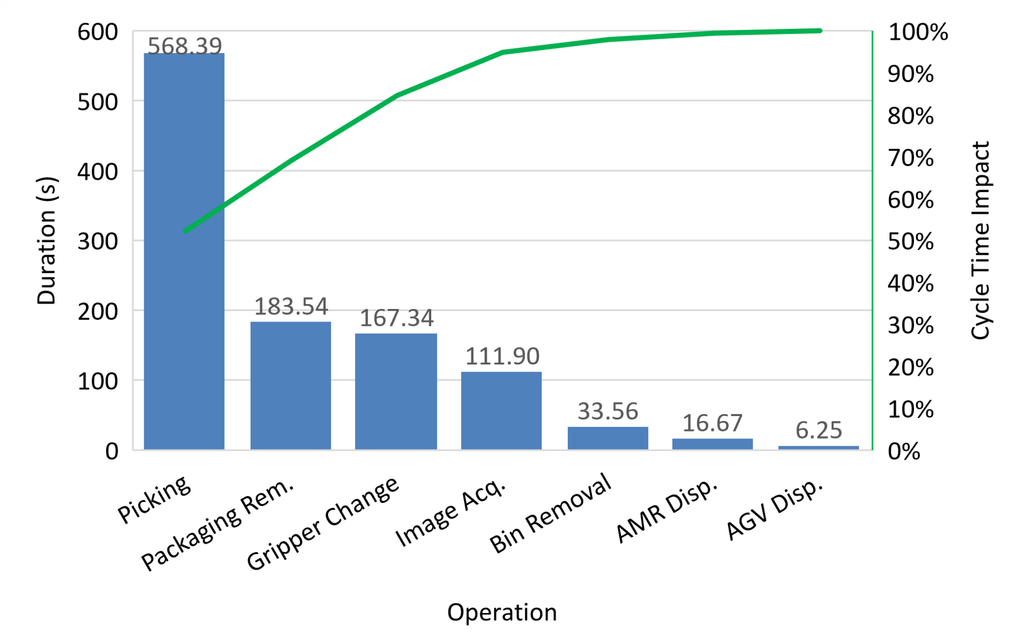
4.3.2 Impact from the Batch Size

Figure 4.10 highlights that cycle times in both the robotic and collaborative areas are impacted by an increase in batch size. This trend has been previously observed with the Asynchronous Hybrid Kitting System. Consequently, the total cycle time also increases. It is worth noting that the rate of increase in total cycle time is greater than that of the cycle times in the two kitting areas. This is due to the longer preparation time required for kit boxes when there are more kits to prepare, which aligns with the characteristics of this system.

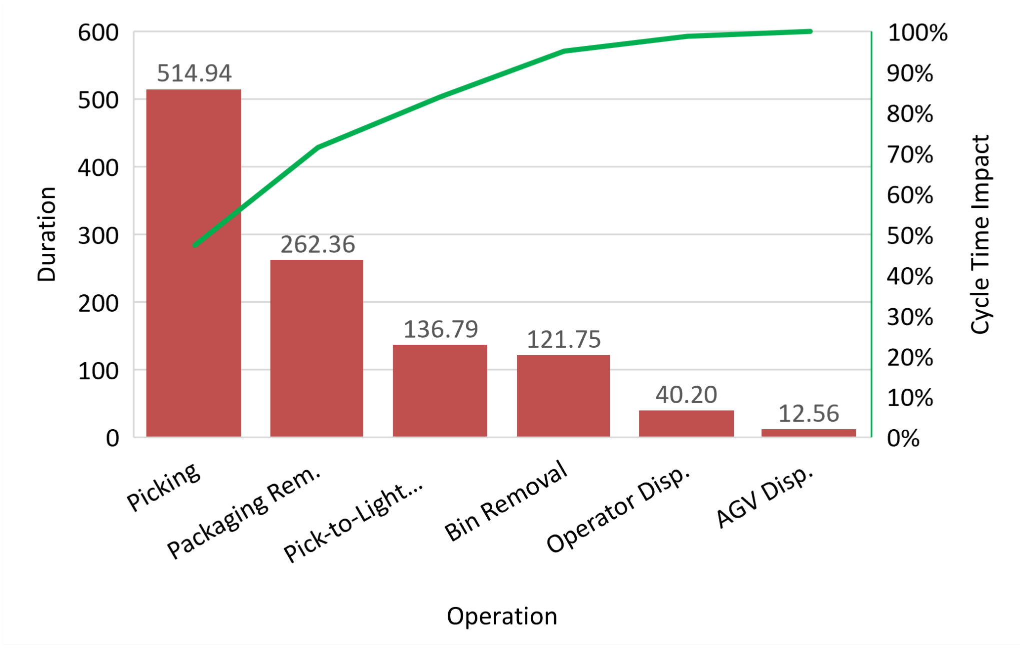
From Table 4.7, for a higher BS value there is a greater allocation of SKUs to the collaborative side, similar to the previous kitting system. This is because the human operator primarily has a higher picking speed when compared to the AMR and the fixed manipulator. In the graph in Figure 4.11, it is observed a greater variation in the total cycle time when transitioning from a BS of 1 to 2. It tends to decrease, stabilizing at around 10% for each unit increase in batch size, similar to what was observed in the Asynchronous Hybrid Kitting System.

4.3.3 Impact from the Picking Errors

Picking errors in the robotic area of the Sequential Hybrid Kitting System can occur in various operations, such as picking SKUs from the bins (PE_i), picking empty bins from the shelves (PE_{bin}), handling interlayer sheets within the bins



(a) Robotic cycle time operations.



(b) Collaborative cycle time operations.

Figure 4.9: Characterization of Sequential Hybrid Kitting cycle time in the optimal assignment.

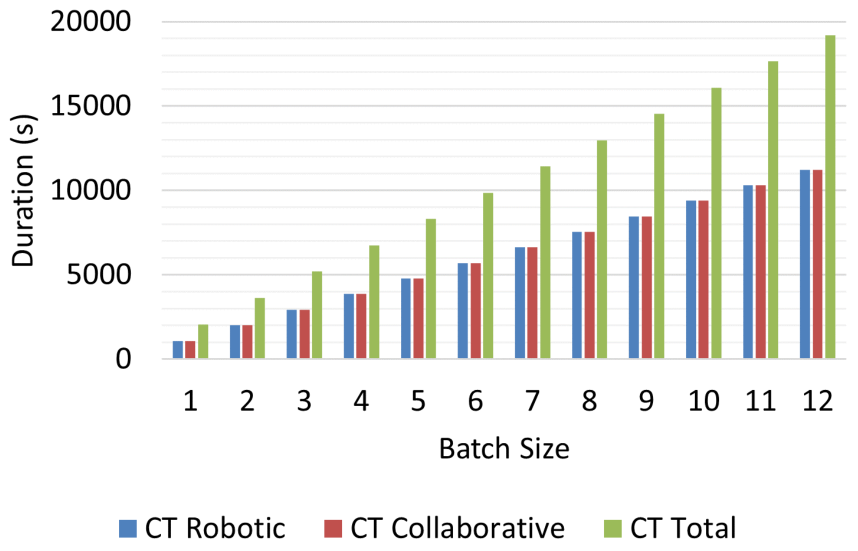


Figure 4.10: Robotic, collaborative, and total cycle times according to the batch size for the Sequential Hybrid Kitting System.

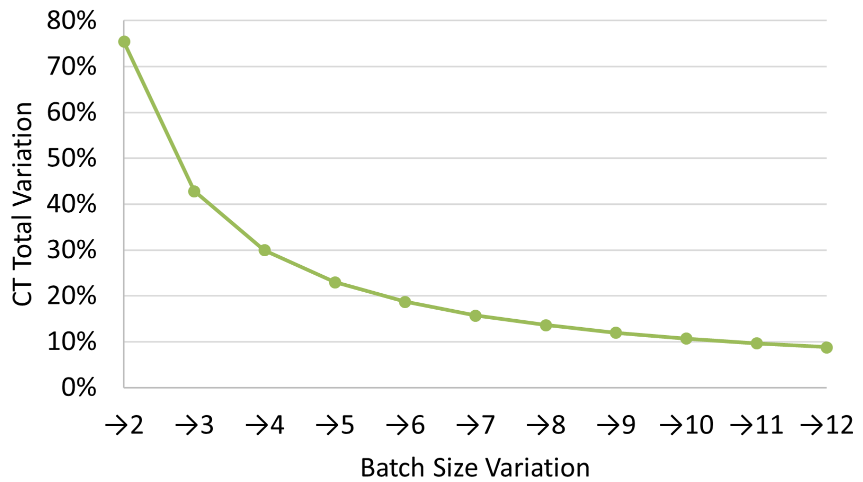


Figure 4.11: Total cycle time percentage variation according to the batch size for the Sequential Hybrid Kitting System.

Table 4.7: Impact from the batch size on cycle times and SKU allocation for the Sequential Hybrid Kitting System.

BS	CT_{total} (s)	#SKUs Robotic	#SKUs Collab.	N_{kits}
1	2073.378	36	129	199
2	3638.411	27	138	398
3	5197.538	20	145	597
4	6755.915	24	141	796
5	8311.290	22	143	995
6	9867.070	19	146	1194
7	11421.499	17	148	1392
8	12979.018	19	146	1591
9	14533.461	18	147	1790
10	16089.438	17	148	1989
11	17645.007	18	147	2188
12	19199.443	17	148	2387

($PE_{interlayer}$), and picking bin dividers ($PE_{divider}$). These errors were analyzed in conjunction for values ranging from 1% to 50%, similar to the previous kitting system.

The results presented in Table 4.8 indicate that the cycle times for both the robotic and collaborative areas are evenly balanced across all PE values. An increase in picking errors led to longer cycle times. Consequently, there is some adjustment in the distribution of SKUs between the kitting areas. Nevertheless, this variation is not as pronounced as in the previous kitting system, which has resulted in a more consistent performance.

Table 4.8: Impact from picking errors on cycle times and SKU allocation for the Sequential Hybrid Kitting System.

PE	CT^R (s)	CT^C (s)	CT_{total} (s)	#SKUs Robotic	#SKUs Collab.
1%	1079.595	1080.250	2062.525	39	126
2%	1081.562	1082.477	2065.420	38	127
5%	1087.647	1088.598	2073.378	36	129
10%	1097.485	1097.561	2085.029	41	124
20%	1111.269	1113.847	2106.202	40	125
30%	1128.349	1128.327	2125.054	37	128
40%	1141.259	1141.765	2142.494	36	129
50%	1154.742	1154.309	2159.364	36	129

Figure 4.13a shows an increase in the duration of the picking and image acquisition operations in the robotic area. It is worth noting the decrease in the duration of the packaging removal operation for a 10% PE, where the reallocation of components with packaging items occurred in the collaborative area, leading to an increase in SKUs assigned to the robotic side, as shown in Figure 4.12. In Figure 4.13b, it can be observed a more substantial increase in the duration of the picking operation due to SKU reassignment.

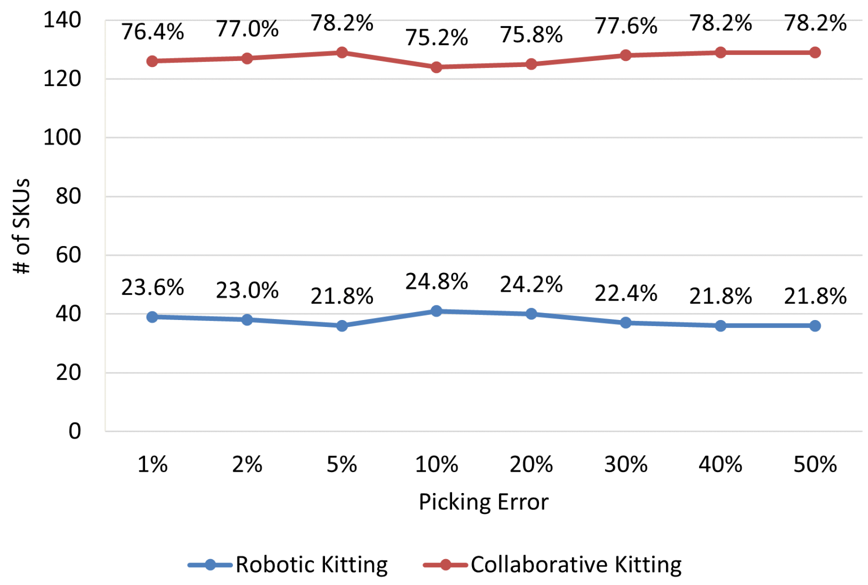


Figure 4.12: SKU allocation according to the robotic picking errors for the Sequential Hybrid Kitting System.

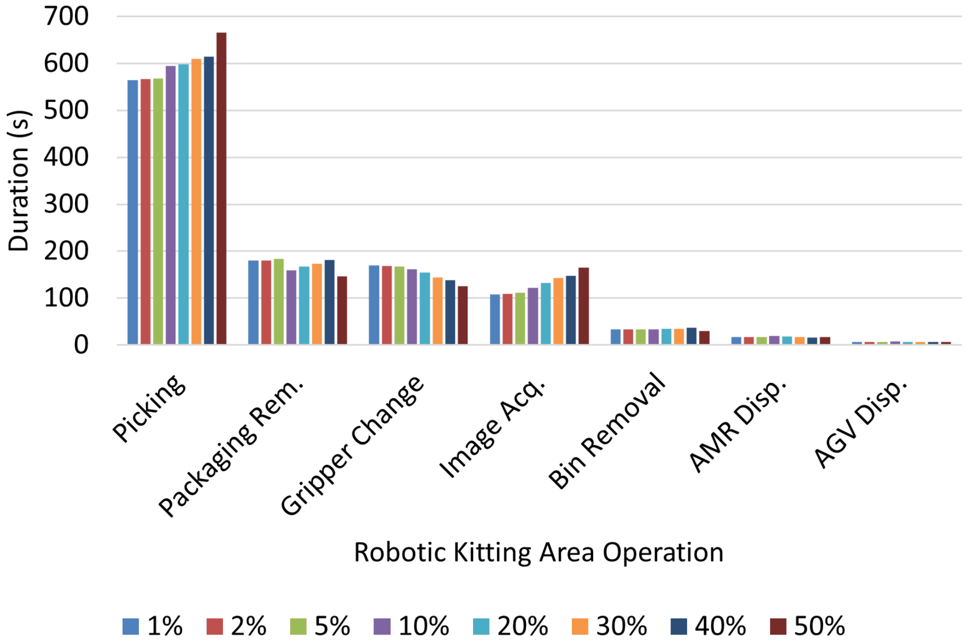
4.3.4 Impact from Simultaneous Picking

Analyzing the impact of simultaneous picking of multiple SKUs by the operator in the collaborative area for the Sequential Hybrid Kitting System, Table 4.9 shows that a 25% penalty in *sim* leads to a 21.2% increase in the total cycle time. This shows a more significant impact than the same penalty in the previous kitting system (which represented a 17.8% increase in cycle time). In cases in which simultaneous picking is improved, a reduction is observed in robotic and collaborative cycle times and, consequently, the overall cycle time, as expected. There is always a higher percentage reduction in this kitting system compared to the previous one. This highlights the importance of kitting area managers to focus on efficient picking methodologies to increase the capacity of operators for simultaneous picking when implementing this system.

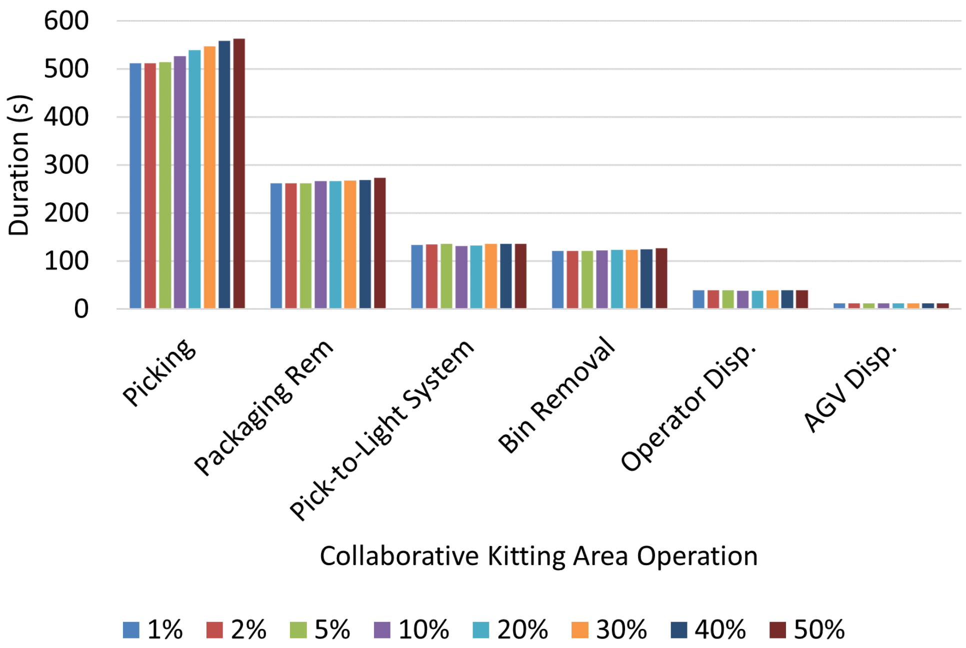
Table 4.9: Impact from simultaneous parts picked by the operator on cycle times and SKU allocation for the Sequential Hybrid Kitting System.

sim	CT^R (s)	CT^C (s)	CT_{total} (s)	Var CT	#SKUs Rob.	#SKUs Collab.
-25%	1426.658	1426.420	2512.856	21.2%	52	113
0%	1087.647	1088.598	2073.378	-	36	129
25%	1001.599	1002.297	1961.186	-5.4%	41	124
50%	866.766	866.882	1785.147	-13.9%	43	122
75%	820.967	821.040	1725.552	-16.8%	40	125
100%	746.153	746.234	1628.304	-21.5%	39	126

From Figure 4.14a, it is observed a generalized reduction in operations in the robotic area, as expected due to the allocation of more components to the collaborative area. In Figure 4.14b, a reduction in the duration of the picking and packaging removal operations can be seen in the collaborative kitting area, which are



(a) Robotic cycle time.



(b) Collaborative cycle time.

Figure 4.13: Robotic and collaborative cycle times according to picking errors by the AMR(s) and fixed manipulator for the Sequential Hybrid Kitting System.

the operations where simultaneous picking occurs.

4.3.5 Impact from the Number of AMRs and Operators

Given that both kitting systems are based on the same modeling foundation for kitting operations, it is expected that the behavior of total cycle time in relation to the number of AMRs and operators would exhibit a similar pattern for both systems. This expectation is confirmed when observing Figure 4.15, where it can be noticed that the impact of the number of operators is more significant than the impact of the number of AMRs.

Increasing the number of operators in the kitting area results in a larger reduction in CT_{total} than increasing the number of AMRs. Therefore, it can be inferred that allocating more human operators brings more efficiency and competitiveness to the kitting system considered, especially if the characteristics of the AMRs are not improved to make them faster in their operations.

4.3.6 Impact from the Collaborative Kitting Cycle Delay Parameter

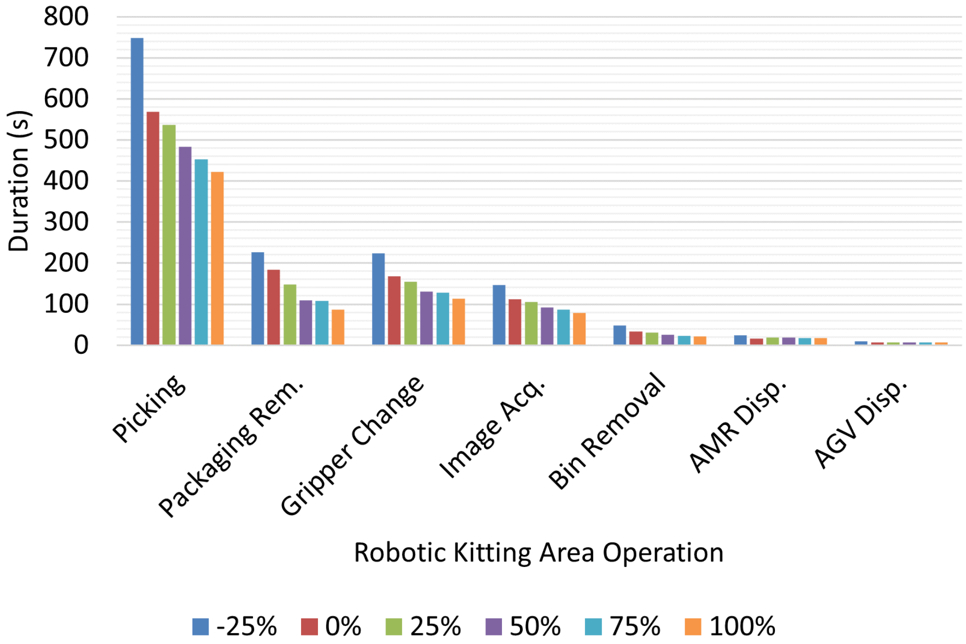
Parameter α present in the total cycle time is a crucial factor reflecting the delay between the start of operations in the collaborative and robotic areas. It plays a significant role in determining the overall efficiency of the system.

As α increases, it signifies a longer delay before operations begin in the robotic area relative to the collaborative area, leading to a higher total cycle time (Figure 4.16). In this way, it is essential to ensure that the first AGVs with the first kits being mounted are dispatched before starting to mount other kits, guaranteeing the smooth progression of operations across the entire system to ensure that α is as small as possible.

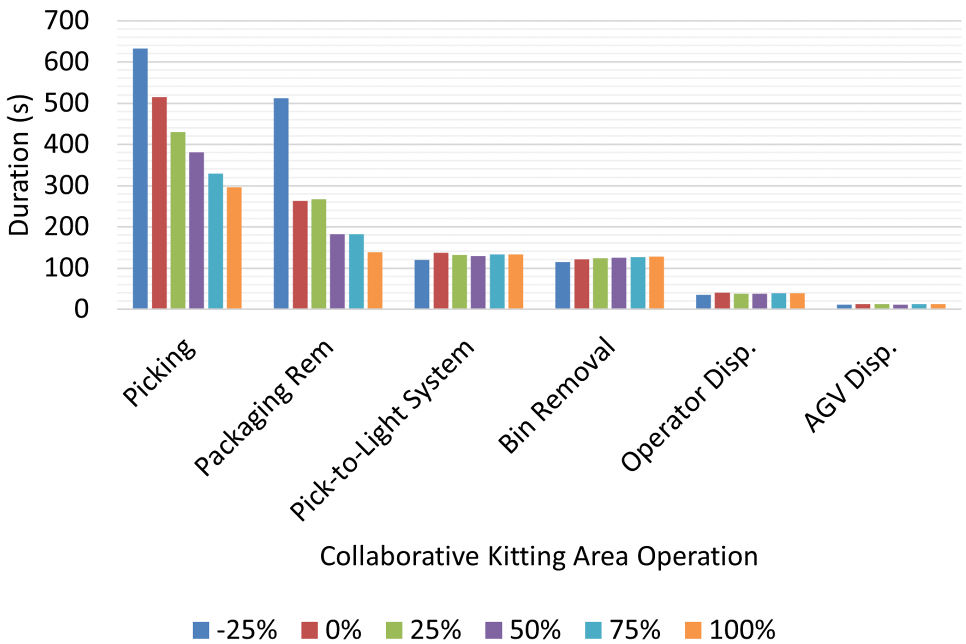
4.4 Scenario Analysis

To completely evaluate the proposed kitting systems, simulations were conducted for various scenarios concerning the allocation of SKUs. This approach allows for an understanding of which scenario results in a more competitive and efficient cycle time. Therefore, for both the Asynchronous and Sequential Hybrid Kitting Systems, the following scenarios were considered:

- **Optimal Assignment**: Allocation of components obtained through the models.
- **High SKU Allocation to Robotic**: Allocation of all components to the robotic kitting area, except for components that include foam protections, plastic bags, or those not suitable for robotic picking.



(a) Robotic cycle time.



(b) Collaborative cycle time.

Figure 4.14: Robotic and collaborative cycle times according to simultaneous picked parts by the operator for the Sequential Hybrid Kitting System.

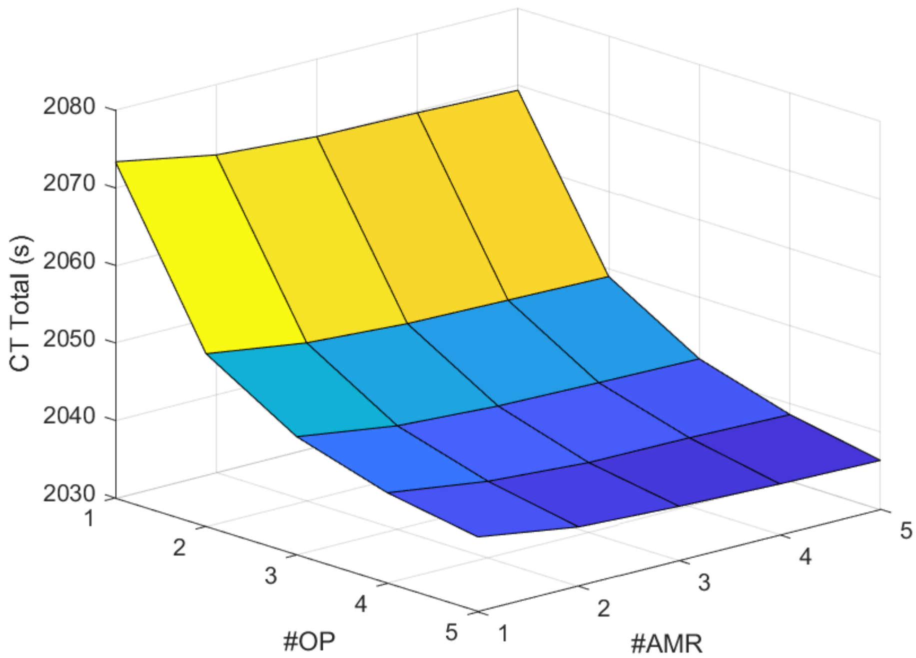


Figure 4.15: Total cycle time according to the number of AMR and Operators for the Sequential Hybrid Kitting System.

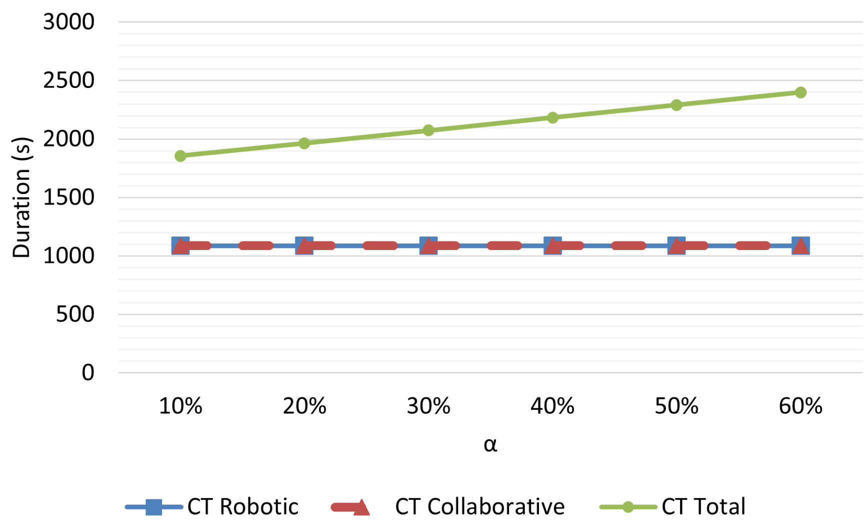


Figure 4.16: Robotic, collaborative and total cycle times according to the parameter α for the Sequential Hybrid Kitting System.

- **High SKU Allocation to Collaborative**: Allocation of all components to the collaborative kitting area.

Analyzing Figure 4.17, it becomes evident that, for the Asynchronous Hybrid Kitting System, the allocation of SKUs obtained through the model results in a shorter cycle time compared to the other two scenarios. In the "high SKU allocation to the robotic area" scenario, 76.4% of SKUs are allocated to the robotic area, and 23.6% to the collaborative area (see Table 4.10). However, the slower picking speed of the AMR significantly penalizes the cycle time, resulting in a duration of 2.5 times longer compared to the Optimal Assignment scenario. In the high SKU allocation to the collaborative area" scenario, where all components are allocated to the collaborative area, avoiding the need to separate the warehouse into two kitting areas, the cycle time increases by 26.9% compared to the Optimal Assignment scenario.

When analyzing the Sequential Hybrid Kitting System, it is evident that the Optimal Assignment of SKUs results in the most efficient cycle time. This approach is 2.8 times faster than assigning a greater number of SKUs to the robotic side and 20.5% faster than assigning all SKUs to the collaborative area.

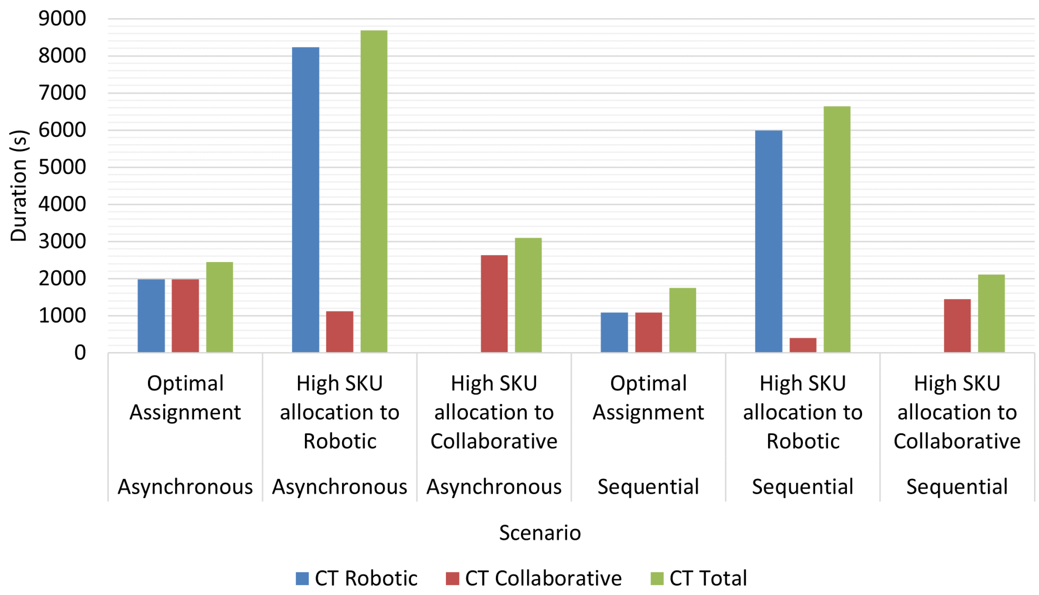


Figure 4.17: Robotic, collaborative, and total cycle times in SKU allocation scenarios for the two hybrid kitting systems.

Comparing the two systems overall, it is evident that the assembly line concept underpinning the sequential system offers advantages, as it leads to shorter cycle times in all three scenarios of SKU allocation.

The scenario that achieved the shortest total cycle time was the Optimal Assignment for the Sequential Hybrid Kitting System, which was 28.4% shorter than the Optimal Assignment for the Asynchronous Hybrid Kitting System for the given input data. Therefore, warehouse managers and decision-makers should choose this system for implementation, taking into account the data considered, if their primary objective is to minimize kit preparation cycle time.

Table 4.10: SKU allocation in the kitting areas for the scenarios considered.

Kitting System	Scenario	#SKUs Robotic	#SKUs Collab.
Asynchronous	Optimal Assignment	46 (27.9%)	119 (72.1%)
	High SKU allocation to the robotic area	126 (76.4%)	39 (23.6%)
	High SKU allocation to the collaborative area	0 (0%)	165 (100%)
Sequential	Optimal Assignment	36 (21.8%)	129 (78.2%)
	High SKU allocation to the robotic area	126 (76.4%)	39 (23.6%)
	High SKU allocation to the collaborative area	0 (0%)	165 (100%)

However, if there are significant quality issues in kit assembly, the Asynchronous Hybrid Kitting System should be considered because it provides more stringent supervision, including a sorting zone that allows for kit verification before they are sent to the assembly line, enabling more effective upstream identification of issues.

Therefore, to select the best hybrid kitting system, the outputs of the models for specific cases must be evaluated to enable a detailed analysis for the particular application.

Chapter 5

Energy Consumption of AGVs in Robotic Kitting

The importance of energy-efficient practices in industrial automation has grown exponentially in recent years, driven by environmental concerns and the pursuit of cost-effective manufacturing solutions. Optimizing energy consumption is important to enhancing operational sustainability and competitiveness in modern manufacturing, particularly in the automotive industry, where efficiency and precision are paramount. This chapter explores the energy dynamics of Automated Guided Vehicles (AGVs) within the domain of robotic kitting in the automotive sector, being a pioneer work, to the best of our knowledge, in exploring the impact of the distance traveled and the number of trips made in the kitting process on the energy consumption of AGVs[1].

This chapter aims to shed light on the intricate relationship between the energy consumption of AGVs and the automated kitting process. It presents a comprehensive Integer Programming (IP) model designed to optimize the robotic kitting process in industrial automotive settings. Robotic kitting, involving the efficient assembly and preparation of kits using automated systems, plays a crucial role in modern manufacturing facilities. The formulation of the mathematical programming model allows for the consideration of flow-related activities, improving the adaptability and flexibility of the kitting process to varying order patterns. Numerical experiments demonstrate the effectiveness of the model in achieving key insights into the energy demand of the AGVs, contributing to advancements in mapping this process in industrial automation and logistics.

The reduced evaluation in research of fully robotic kitting systems makes it essential to focus on developing and analyzing a layout incorporating Autonomous Mobile Robots (AMRs) for picking and AGVs for kit assembly. By integrating these robotic technologies, we seek a comprehensive and automated kitting process to optimize operational performance and reduce manual non-value-added

[1]The contribution presented in this chapter has been accepted to be published in the conference proceedings of the Sixth Iberian Robotics Conference (ROBOT2023) that will be published by Springer Lecture Notes in Networks and Systems series, titled "Optimization of the Energy Consumption for Robotic Kitting in the Automotive Industry", authored by Mário Simões, Telmo Pinto and Cristóvão Silva.

tasks. Due to the limited adaptability of robots in manufacturing processes, minimizing the number of trips they perform becomes crucial to reducing entropy in the system and reducing energy consumption.

At the heart of the investigation, the IP model considers critical operations analogous to the ones presented in Chapter 3 of this dissertation. These include the time required for kit box preparation on AGVs, the duration of picking operations executed by Autonomous Mobile Robots (AMRs), the intricacies of image acquisition and processing, travel times for both AMRs and AGVs, and the temporal aspects of empty component bin removal by AMRs. The primary objective is unequivocal: to minimize the energy footprint of AGVs in the kitting process, amplifying operational sustainability while upholding the utmost precision in kit assembly.

5.1 Robotic Kitting System

5.1.1 Layout Description

The layout presented in Figure 5.1 for the robotic kitting system comprises a two-sided shelving area, i.e., two facades, both of equal length. Each shelving unit consists of three levels, with the first two levels designated for storing the components required for kit assembly, while the third level houses the ramps for evacuating empty bins to be subsequently replenished.

The kitting process involves the use of an Automated Mobile Robot (AMR), a computer-controlled and wheel-based with a manipulator fixed on its top, which automatically moves in the warehouse by a combination of software and sensor-based system, responsible for retrieving the necessary components from the shelving units and placing them into the kits located on the Automated Guided Vehicle (AGV). The AGV is a robot equipped with multiple kit boxes designed to receive and hold the components constituting a kit. In this system, the AGV follows a fixed path, consistently in the same direction. Upon completing its route through the storage area, the AGV advances to the border of line to fulfill the kit requests made during the production planning process.

Based on information gathered from an automotive manufacturer, warehouse experts, and scientific papers concerning this subject, the racks used have standard lengths installations, where the bins with the different Single Keeping Units (SKUs) are positioned, which involves an effective bin allocation. These bins contain parts that can be arranged in partitions made with separators or in bulk for the case of smaller pieces. The variability in SKU characteristics is related to several aspects, such as their material (metal, plastic, rubber), flexibility, shape, dimensions, and weight.

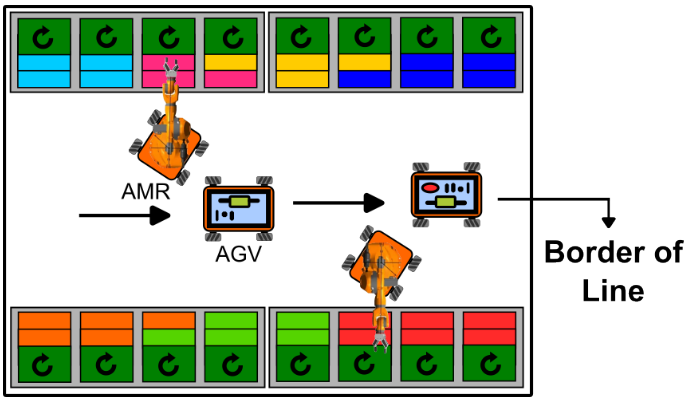


Figure 5.1: Schematic representation of the kitting system considered.

5.1.2 Kitting Process

The kitting process in the robotic system considered consists of a set of carefully coordinated steps that ensure the efficient and accurate assembly of kits, as presented in Figure 5.2. The process starts with the Automated Mobile Robot (AMR) receiving the order, the bill of materials (BOM) ,specifying the required components for the kit assembly. Subsequently, the AMR navigates to the designated shelving unit where the desired part is stored. To identify the exact position of the component to be picked, the AMR performs image acquisition, utilizing advanced vision systems to detect and locate the specific part. Once the element is identified, the AMR executes its gripping mechanism to grasp the piece securely and subsequently places it into the corresponding kit, which is positioned on the Automated Guided Vehicle (AGV).

The AMR is preparing multiple kits at the same time, sorting the parts to the correct kit, ensuring the proper kit assembly, and avoiding the need to have a sorting system before following to the border of line or completing one kit at a time, which leads to an increased travel time needed. The AMR and AGV work in tandem throughout the kitting process. While the AMR continues to complete the kits by picking and placing the required components, the AGV moves alongside the AMR, following its designated route. This seamless collaboration ensures a continuous flow of component retrieval and kit assembly. Upon completing the preparation of all required kits, where the kits are ready for further assembly or distribution, the AGV will then move to the border of line. After completing the assembly of kits and the departure of the AGVs, the AMR will pick up empty bins from the racks and relocate them to the third level, where the evacuation bin is located. This final step marks the conclusion of the kitting process, and a new AGV should be ready to receive parts and assemble new kits.

5.1.3 Mathematical Model

The model considered analyses the cycle time needed to pick all the SKUs required to form the kits according to the BOM to minimize the energy needed by the AGVs to transport all the kits in a reference period that represents the average

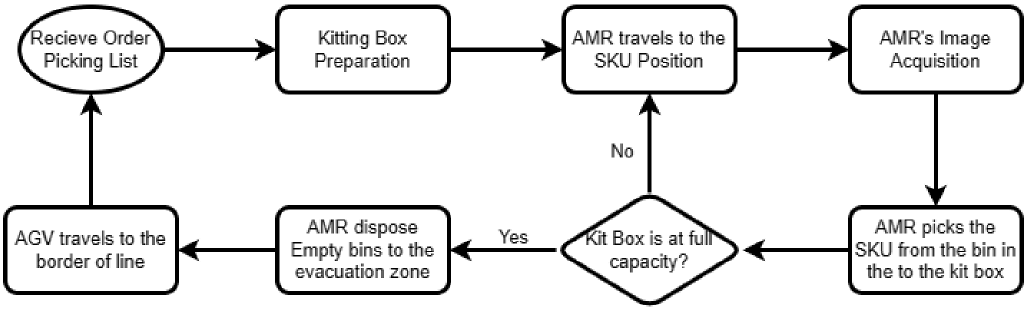


Figure 5.2: Diagram with the kitting processes developed.

demand of components in a kitting zone for the automotive industry, adequate to the number of end products assembled in the production line. To formulate this model, it is essential to assume that the kitting process can be considered independent of the processes upstream and downstream of the kitting system. The upstream processes represent replenishing empty component bins with new full bins, avoiding accumulation in the evacuation ramp. The downstream processes include the usage of kits from the AGV, freeing the AGV to return to the warehouse to fulfill new kit orders. In the sequel, parameters, decision variables, and the integer programming model are presented. For all the cases, i represents a single SKU ($i \in [1, 2, ..., Z]$, where Z is the total number of SKUs needed to build the kits).

Parameters

- t_{kp}: time needed to prepare a single kit box (s);
- t_{im}: time needed for the AMR to perform an image acquisition to locate the component in the bin (s);
- t_{p_i}: time needed for the AMR to pick a single SKU i from the bin to the kit box (s);
- t_{bin}: time needed for the AMR to return and pick up the empty bin and place it in the evacuation ramp (s);
- T_{lim}: temporal window available to proceed with kitting tasks (s).
- PE: parameter describing the AMR's picking error probability on picking components;
- PE_{bins}: parameter describing the AMR's picking error probability on picking empty bins;
- v_{AMR}: average AMR's velocity considered (m/s);
- N_{AGV}: number of AGVs available for the kitting operation;
- v_{AGV}: average AGV's moving velocity considered (m/s);
- L_{Kits}: maximum number of kit boxes that AGVs can support;

- Bg: parameter describing the image acquisition performed in the background;
- m: parameter describing the electrical power of the AGV in function of the weight transported (W/kg);
- b: parameter describing the electrical power of the AGV when it is empty (W).
- M_{kit}: maximum weight supported in the kit box (kg);
- M_i: weight of SKU i (kg);
- Vol_{kit}: maximum volume supported in the kit box (m^3);
- Vol_i: volume of SKU i (m^3);
- BW_i: Bin's width of SKU i (m);
- n_i: number of components of SKU i in the bill of materials;
- N_i: number of components of SKU i in one full bin;
- N_{levels}: number of levels in the racks present in the robotic kitting area;
- S: standard spacing between bins in the racks (m);
- t_{BOL}: time needed for the AGV from the warehouse to the border of line (s);
- F: Number of facades in the warehouse.

Decision Variables

- N_{kits}: Number of kits carried by the AGV on each trip to the BOL;
- N_{AGV_trips}: Number of AGV trips to deliver all the kits to the BOL;
- CT: Total cycle time of the robotic kitting process (s);
- P: Electrical power required for operating the AGVs (s).

Integer Programming Model

$$minimize\ E = P \cdot \left(T_{AGV\_travel} + T_{BOL} \cdot N_{AGV\_trips}\right) \tag{5.1}$$

Subject to:

$$CT \geq T_{kit\_prep} + T_{image} + T_{AMR\_pick} + T_{AMR\_travel} + T_{AGV\_travel} + T_{bin\_rem} \tag{5.2}$$

$$CT \leq T_{lim} \tag{5.3}$$

$$T_{kit\_prep} = N_{kits} \cdot t_{kp} \tag{5.4}$$

$$T_{image} = \sum_{i=1}^{Z} t_{im} \cdot (1 + PE)(1 - Bg) \tag{5.5}$$

$$T_{AMR\_pick} = \sum_{i=1}^{Z} t_{p\_i} \cdot n_i \cdot (1 + PE) \tag{5.6}$$

$$T_{AMR\_travel} = \frac{\sum_{i=1}^{Z} BW_i + S}{N_{levels} \cdot v_{AMR}} \tag{5.7}$$

$$T_{AGV\_travel} = \frac{\sum_{i=1}^{Z} BW_i + S}{N_{levels} \cdot v_{AGV} \cdot F} \tag{5.8}$$

$$T_{bin\_rem} = \sum_{i=1}^{Z} \frac{n_i \cdot t_{bin}}{N_i} \cdot (1 + PE_{bin}) \tag{5.9}$$

$$N_{kits} \geq \frac{\sum_{i=1}^{Z} n_i \cdot M_i}{M_{kit}} \tag{5.10}$$

$$N_{kits} \geq \frac{\sum_{i=1}^{Z} n_i \cdot Vol_i}{Vol_{kit}} \tag{5.11}$$

$$N_{AGV\_trips} \geq \frac{N_{kits}}{L_{kits} \cdot N_{AGVs}} \tag{5.12}$$

$$P = (m \cdot (L_{kits} \cdot M_{kit}) + b) \cdot N_{AGVs} \tag{5.13}$$

$$N_{kits}, N_{AGV\_trips}, CT, N_{AGVs} \geq 0 \tag{5.14}$$

The objective function (5.1) aims to find the optimal required energy for AGV to take the kits to the BOL, considering an arrangement of kits on the AGVs and the allocation of kits to AGVs that minimizes this electrical energy, where it is based on the relation between electrical energy and Power $E = P \cdot t$, where the time depends on the number os AGV trips performed. The process becomes more efficient by minimizing energy consumption, reducing the energy impact of kitting, and improving overall production efficiency for automotive manufacturers.

The cycle time of the kitting process is given in (5.2): the five operations are considered, defining the minimum value for the kitting cycle time. As the kitting operations need to occur in a time frame compatible with all the other activities in the automotive manufacturer, the maximum duration is defined, limiting the value of the cycle time in (5.3). In view of each kitting process formulation and taking into account the assumptions presented in Table 5.1, a set of constraints is defined, where Equation 5.4 characterizes the time needed by the AMR to prepare the AGV with the kit boxes to accommodate the SKUs present in the BOM, considering the time for each kit box preparation, applied to all the kit boxes needed. Equation 5.5 gives the time required for all the SKUs to the AMR system to capture and process a picture of the bin to locate the component to proceed with the picking task, which is penalized by the fact that AMR can fail at picking parts at first attempt, needing to take a new image of the bin. As part of this image processing can happen in background time, the term $(1 - bg)$ aims to reduce this time when this scenario occurs. Equation 5.6 performs the determination of the duration of time for the AMR to pick all the SKUs in the BOM, increased by

Table 5.1: Assumptions considered for the Robotic Kitting System.

Operation	Assumption
Kit Preparation	-The AMR can pick the kit boxes; -t_{kp} includes traveling, picking, and placing the kit boxes in the AGV.
Picking	-The AMR picks one part at a time; -$t_p i$ includes picking, rotation, and placing the SKU i in the kit box; -The AMR can fail at picking parts.
Vision	-Image acquisition always occurs before picking apart; -Image acquisition by the AMR can occur as a background process.
AMR Travel	-The AMR moves through the entire storage area in each preparation cycle; -v_{AMR} in an average between its initial speed, limit speed, and final speed; -The storage zone has two facades.
AGV Travel	-The AGV is near the AMR to receive picked parts; -When the AGV is full, it moves to the border of line; -v_{AGV} in an average between its initial speed, limit speed, and final speed;
Empty Bin Removal	- In a cycle time, it is consumed full bins; - The AMR can fail at picking empty bins; - The evacuation ramps are located at the third level of the rack.

the factor $(1 + PE)$ considering the failure rate obtained for the AMR to properly pick components correctly, always using the same gripper to avoid the existence of gripper setup times, where $t_{AMR\_pick\_i}$ depends on the SKU which is being picked. Equation 5.7 defines the time needed for the AMR to travel through the aisle, considering the total distance traveled by it, obtained by the width of the bins and the average spacing between them, and its average velocity (also taking into account the number of levels in the rack). Equation 5.8 considers the time the AGV needs to travel with the kits completed to the Border of Line (BoL). Finally, Equation 5.9 defines the duration of the bin removal process for all the empty bins present, considering that the AMR can fail at picking container, where $(1 + PE_{bin})$ penalizes this time.

On the other hand, (5.10) and (5.11) represent operational constraints to assure that the number of kit boxes mounted can stand the physical and imposed limitations on the kit boxes relative to their maximum weight and volume capacities, respectively. Equation 5.12 guarantees the determination of the total number of AGV trips needed to complete the kitting process for all the N_{kits} mounted. Finally, (5.13) defines the electrical power consumed by the AGV for the weight it can carry, $L_{kits} \cdot M_{kit}$, taking into account a linear fit for a set of weights and respective powers by an AGV, for a set of experimentally obtained data (Meißner and Massalski, 2020).

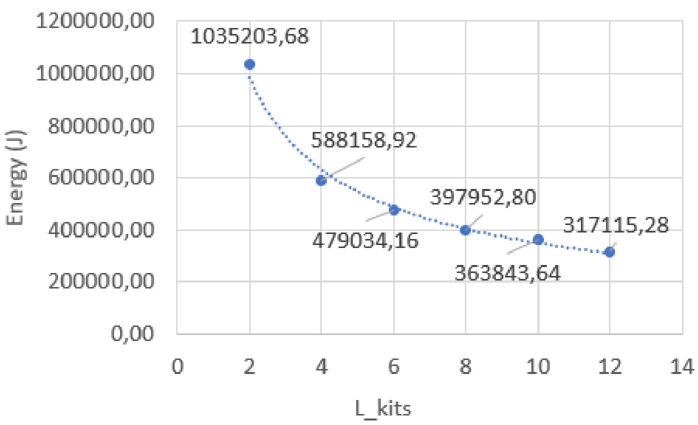
5.2 Numerical Analysis of the Model

The IP model was implemented in a PC (Intel Core i7 @ 2.6 GHz and 32 GB RAM) and using the CPLEX Python API. The results were obtained in milliseconds. A case study based on the automotive manufacturer application is now tested, considering realistic data of 165 SKUs. The analysis shows that a significant portion (more than 50%) of the overall process cycle time is spent on two key activities:

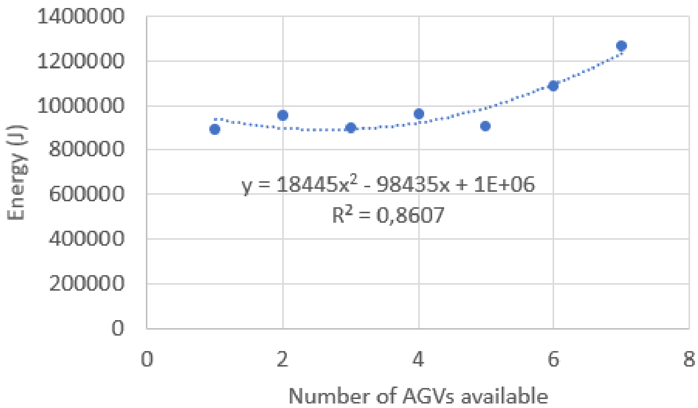
picking the individual components and preparing the kits. The picking process by the AMR accounted for approximately 743 seconds, while the kit preparation took around 264 seconds. These findings emphasize the importance of streamlining and optimizing these stages to achieve overall process efficiency.

Additionally, several tests were conducted to understand the behavior of the model concerning the input data and their impact on the energy required by AGVs. The tests considered an AMR with an average velocity of 1 m/s and a 5% picking error for both components and bins, while the AGV was defined to have a speed of 0.8 m/s. The simulations also considered a 10 cm spacing between containers and two facades in the warehouse to represent real-world conditions accurately.

In Figure 5.3a, the relationship between energy consumption and the limit of kits carried by AGVs is depicted, assuming the presence of two AGVs in the warehouse. The graph demonstrates that energy consumption decreases as the AGV can carry more kits on each trip. This suggests that consolidating more kits onto a single AGV reduces the required number of trips, leading to lower energy consumption. However, the potential energy savings become less significant beyond a certain limit (approximately eight kits per AGV), indicating diminishing returns.



(a) Energy VS Limit of Kit carried by AGVs.



(b) Energy VS Number of AGVs available.

Figure 5.3: Energy Consumption in the Robotic Kitting Process.

Figure 5.3b illustrates the relationship between energy consumption and the number of AGVs. Considering that each AGV consumes energy while traveling and performing kitting tasks, a higher number of AGVs require more energy to support their operations; the energy is penalized because the reduction in the number of trips performed doesn't compensate for the increase in electrical power required by having more AGVs. On the other side, for few AGVs available, as the number of AGVs increases, the energy consumption doesn't vary considerably, which was expected because adding an AGV reduces the number of trips performed. Performing a quadratic approximation to the data, it is observed that for the 165 SKUs and 88 kits being created, the optimal number of AGVs would be two or three.

The results highlight the trade-off between the number of kits per AGV and the number of AGVs needed for efficient kitting operations. A careful balance must be struck to optimize energy consumption while ensuring timely and accurate kit assembly in the cycle time available. The IP model allows decision-makers to determine the optimal combination of these factors based on their specific operational requirements and constraints.

Chapter 6

Conclusion

This concluding chapter aims to provide a broad analysis of the work undertaken in this dissertation, where it summarizes the main accomplishments, drawing key findings from the research presented in preceding chapters. Furthermore, it discusses the practical contributions and managerial insights from the models developed, showing their significance in the overall context of the field. Additionally, this chapter identifies potential future research and development areas, outlining possible directions for further exploration and improvement. This work aimed to contribute to operations research and inspire advancements in innovative kitting layouts.

Kitting demonstrated to be a successful strategy for parts feeding to assembly lines featuring high variation, particularly in the automotive industry. High variation requires an increased storage space near the Border of Line (BoL), extending travel and search times. Kitting mitigates these inefficiencies by decreasing travel times, optimizing storage space at the BoL, and consequently enhancing the quality of the End Products (EPs).

6.1 Main Accomplishments

After analyzing the research literature on the different explored types of kitting systems, understanding the challenges faced by the automotive factory located in Portugal, and perceiving the limits of previous kitting layouts, two proof of concept layouts were presented to improve the kitting process.

The Asynchronous Hybrid Kitting (AHK) System layout with two semi-independent kitting areas, taking the benefits of both the robotic performance on kitting and the fast adaptability of the human operators, presenting the following features:

- **Pickers traveling time reduced**, having a nearby AGV to serve a box to place the picked components, allowing separation of picking components from the storage rack and moving components to the correct kits;
- **Flexibility increased**, in the case of introduction of a new EP, new compo-

nents can be allocated to the adequate kitting zone;

- **Improved Capacity**, with the tugger train working as a buffer, allowing both robotic and collaborative kitting areas to complete different kits simultaneously;
- **Enhanced quality control**, having the picker responsible for selecting the components and a sorting area where a thorough double-check is performed to ensure the kits contain all the necessary parts. This reduces the probability of sending incomplete kits to the BoL or incorrect parts being included in a kit.

Already in the Sequential Hybrid Kitting (SHK) System, this layout brings the concept of the production line to the kit formation process, presenting the following features:

- **Compact layout**, where AGVs carry the final kit boxes, eliminating the need to allocate space for the sorting operation, making this kitting system ideal for warehouses with more demanding space limitations;
- **Reduced number of operations**, improving the overall process efficiency without needing to sort the components involving the picking from the AGVs to the kit;
- **Simpler technical configuration**, compared to the AHK System since there are only AMRs and AGVs operating, eliminating the need for programming and setup of a Tugger train in the warehouse, being that role performed by the AGVs.

6.2 Contributions and managerial insights

In the context of the developed models, several innovations have been introduced, advancing upon existing literature in the following key aspects:

1. **Impact of the AMRs and Human operators allocated to the kitting area**: A novel aspect of the present models is exploring how the number of AMRs and human operators impacts the overall cycle time of the kitting process, providing valuable insights into workforce allocation and resource optimization.
2. **Distance modeling for pickers**: It introduced a new approach to modeling the distances traveled by pickers along the storage racks, offering a more accurate representation of the real-world operational dynamics, accounting for varying distances between storage locations and the empty space between component bins due to standard rack width sizes.

3. **Evacuation time for empty bins**: The models present the evacuation time for bins, considering that the evacuation area is consistently located on the last level of the racks. This realistic depiction ensures that the evacuation process aligns with practical scenarios.

4. **AGV travel time modeling**: The inclusion of AGV travel time in both kitting areas is a notable contribution, accounting for the time required for AGVs to transport components, enhancing the overall practicality of the models.

5. **Gripper changing time for the AMR and the manipulator**: The time to change the grippers for the AMRs and fixed manipulator was modeled, considering the calibration process necessary for seamless transitions. This detail addresses the practical challenges of such setups.

6. **Pick-to-Light system integration**: The models incorporate the pick-to-light system to support human operators in the component picking process, enhancing human picking efficiency and taking into account the inherent processes in this system.

7. **Kit transport time**: Another significant addition is the inclusion of the time required to send kits to the BoL. This ensures that the entire kitting process is comprehensively captured, from assembly to delivery of kits.

These innovations contribute to a more holistic and practical understanding of kitting operations, enabling better decision-making, resource allocation, and process optimization in real-world manufacturing environments.

Regarding the obtained results, it was possible to conduct a sensitivity analysis to study the impact of various factors on cycle times. The investigation included the effect of batch size, with a tendency for a 10% increase in total cycle time for each unit increase in BS for larger batch sizes. It also considered the impact of picking errors in the robotic kitting areas, which led to a reallocation of SKUs between kitting areas, the influence of simultaneous picking in the collaborative kitting areas by operators, highlighting its considerable impact on SKU allocation adjustments and its contribution to reducing cycle times. Additionally, the impact of the number of AMRs and operators in the kitting areas was examined, revealing that allocating an additional operator provides more competitive advantages in terms of total cycle time than adding another AMR.

For specific characteristics of each system, in the AHK System, a sensitivity analysis was conducted regarding collaboration in the sorting zone, significantly impacting the sorting operation in the robotic area. Thus, this parameter should be set as low as possible while ensuring operator safety during sorting operations. For the SHK System, the parameter α was analyzed, highlighting the importance of implementing a system that ensures kits are completed in a manner similar to First Come, First Served (FCFS) system to always have AGVs with dispatched kits from the robotic to the collaborative area at the beginning, allowing for a small α.

Through scenario analysis, constructive aspects were obtained, such as that optimal assignment for both kitting systems resulted in lower total cycle times, with an advantage for the Sequential system.

These results served as an additional decision support mechanism to understand the differences between the presented hybrid kitting systems for kit preparation, showcasing their characteristics and behaviors in response to the available data. Indeed, the slow speed of AMRs, which results in longer SKU picking times compared to operators, the need to change grippers due to the irregular shapes of components in the automotive industry, and the time required for image acquisition and processing, considering the complexity of the real environment surrounding AMRs, leave room for technological improvement. This improvement in robotics used for kit preparation can enhance the competitiveness of robotic kitting areas, enabling a reduction in the total cycle time of the process.

In chapter 5, it was proposed an IP model offering valuable insights into the energy demand of AGVs in the robotic kitting process. By considering various operational parameters, manufacturers can enhance the adaptability of their automated kitting processes in response to the number of AGV trips performed and the number of kits carried by the AGVs. Implementing the model with adequate datasets can lead to reduced energy consumption, increased productivity, and consequently cost savings in the automotive manufacturing industry. This research contributes to industrial automation and logistics advancements, paving the way for more sustainable kitting operations, setting the stage for a broad exploration of the energy dynamics of AGVs in modern warehouses in the context of Industry 4.0, and serving as a prelude to the in-depth investigation that follows to uncover new insights that will bolster the sustainability and efficiency of modern manufacturing practices.

6.3 Future Work

In terms of future research, it would be compelling to use the models to develop and apply them to new configurations, such as parts-to-picker or even Automated Storage/Retrieval Systems (AS/RSs) in one or both the robotic and collaborative kitting areas, for comparison with new and different scenarios. Additionally, studying the impact of errors related to incorrect bin replenishment in the shelves, modeling incorrect picking by the AMR on the cycle time, and damages occurring to the components during the kitting operations are aspects that will require further investigation to understand its impact on the cycle time of the process. In the collaborative side of kitting systems, it would be valuable to statistically map picking errors since the models developed did not account for picking errors by the human operator.

Applying the models in different industry settings, such as e-commerce warehouses or other sectors dealing with customizable EPs, can provide valuable insights into their generalizability and adaptability beyond the automotive manufacturing context. This exploration can help determine if the principles and methodologies developed in this dissertation can be extended to optimize kitting processes in a broader range of industries, thereby contributing to the advancement of logistics and intralogistics operations in various domains.

The models proposed are quick to obtain solutions, but for applications with very large instances, heuristics could be used for both of the considered hybrid kitting systems. Other alternative approaches should be the development of models that provide a better understanding of the flow of components throughout the ongoing operations of the kitting areas. This would enable enhanced traceability within the process and the warehouse. Furthermore, the application of machine learning models (for example supervised learning models) could improve the successfulness of the MIP models developed by providing better estimates to forecast parameters such as the demand of Stock Keeping Units (SKUs), instead of being a deterministic parameter as it was considered.

Regarding the Fully Robotic Kitting Systems presented in Chapter 5, future research should focus on exploring additional parameters and constraints to fine-tune the model and align it to consider more energy-related aspects inherent to kitting operations. This includes mapping the energy consumption of AMRs in both the displacement and component picking operations, the energy consumption of the tugger train, and the pick-to-light systems. Another interesting aspect for future research is studying the impact of the speed of both AMRs and AGVs on the efficiency of the kitting process and energy consumption.

In conclusion, it becomes increasingly clear that embracing innovative operational research models, whether through advanced MIP approaches or through heuristic models, holds the key to unlocking the full potential of hybrid kitting layouts in the "warehouse of the future". These models, when tailored to analyze processes at a granular level, promise to unveil the intricate materials flow within the warehouses in Industry 4.0. With this knowledge in hand, we can boldly steer towards a future where efficiency, adaptability, and sustainability converge to redefine the very essence of automated warehousing and logistics.

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Appendices

Appendix A

Robotic Kitting Assumptions

Operation	Assumption
Picking/Placing	- The robotic manipulator picks one part at a time. - The bins are small enough to consider that parts stored in the same bin have a similar picking/placing times duration. - Manipulator rotation time is included in the picking/placing time. - The time needed to change parts orientation to better fit in the AGV box is included in the picking/placing time. - The AMR can fail at picking parts at first attempt.
Image Acquisition	- The time duration for image acquisition is an average value and equal to all bins. - Image acquisition occurs always before picking apart. - Image acquisition by computer vision systems can occur as a background process.
AMR Displacement	- The robotic kitting area can have one or more AMR operating simultaneously. - Storage racks have bins added to them so that they can be achievable in AMR's path. - The AMR moves through the entire storage area in each preparation cycle. - The AMR's speed takes into account an average between its initial speeds, limit speed, and final speeds. - No travel speed is needed to remove bins from a rack in the same position but in different rack levels.

AGV Displacement	- The AGV should be available near the AMR, ready to receive the picked parts. - The AGV's speed takes into account an average between its initial speeds, limit speed, and final speeds. - Multiple AGVs, if present, are synchronized to maintain smooth operations and avoid collisions or congestion. - Potential maintenance requirements and planned downtime for the AGVs to maintain operational efficiency occur outside the cycle time. - The AGV has a limited capacity in weight and volume. **For the Asynchronous Hybrid Kitting (AHK) System:** - Once the AGV is fully loaded, it moves to the sorting zone for further processing. - A new AGV is stationed near the AMR to promptly replace the fully loaded AGV and continue the kitting process. **For the Sequential Hybrid Kitting (SHK) System:** - When the kit is completed with the parts allocated to the robotic area, the AGV moves to the collaborative kitting area.
Empty Bin Removal	- In a cycle time it is consumed full bins. - The time for picking empty bins is considered an average value for all types of bins. - The evacuation ramps are located at the beginning or at the end of a rack. - The AMR can fail at picking empty bins on the first attempt.
Sorting	**For the AHK System:** - The fixed manipulator sorts one part at a time. - The tugger train already has the kit boxes placed and ready to receive parts. - The fixed manipulator can fail at picking parts on the first attempt. - The tugger train remains stationary during the positioning of the parts. - The manipulator and operator can work simultaneously.

Packaging Removal	- The Manipulator can remove interlayer sheets and dividers. - The Manipulator can fail at picking interlayer sheets and dividers. - No travel time is needed to remove interlayer sheets and dividers. - The number of items is defined considering that parts consumed are from full bins.
Gripper Change	- The AGV needs to change the gripper to pick different parts, packaging items, and empty bins. - The fixed manipulator needs to pick parts. - The time required to change the gripper is the same for both the AMR and the fixed manipulator when picking a specific part. - The gripper change time includes disconnecting the current end effector, connecting the new end effector, and any additional time required to calibrate or adjust the new end effector. - The time needed for a single tool changes before picking an item, which is influenced by the calibration parameter Cal. - Incorporating storage assignment rules may help optimize the efficiency of tool changes by grouping SKUs that can be picked with the same tool. - The grippers' holder is connected to the base of the robotic arms so there is no travel time needed.

Table A.1: Assumptions considered for the Robotic Kitting Area.

Appendix B

Collaborative Kitting Assumptions

Operation	Assumption
Kit Box Preparation[1]	**For the Asynchronous Hybrid Kitting (AHK) System:** - The human operator in the sorting zone prepares the kit boxes in the tugger train. - Empty kit boxes are within reach for the operator in the sorting zone. - t_{kp} includes the time to pick the kit boxes and place them in the correct position in the tugger train. - The human operator can prepare multiple kit boxes at the same time.
Pick-to-Light	- The time duration for pick-to-light is an average value and equal to all modules. - Pick-to-light module activation always occurs before the operator's picking activity. - Potential communication and picking detection issues may affect the pick-to-light system. - Pick-to-light module batteries are changed during maintenance hours, not in the kitting cycle time. - Operators are alerted to replace pick-to-light module batteries before they run out of power.
Picking	- The human operator can pick multiple parts simultaneously. - The bins are small enough to consider that parts stored in the same bin have a similar picking time. - The time needed to change parts orientation to better fit in the AGV box is included in the picking time. - The operator doesn't fail at picking components.

[1] Operation occurs in the collaborative kitting area only for the Asynchronous Hybrid Kitting (AHK) System.

Operator Displacement	- The collaborative kitting area allows for the presence of one or more operators working simultaneously. - Storage racks have bins arranged on different levels to ensure easy access by the operator. - The operator traverses the entire storage area during each preparation cycle. - The operator's speed is the average value between their initial, limit, and final speeds. - No additional time is required to remove bins from model's parameters within the same position. - No obstacles or obstructions affect the operator's movement.
AGV Displacement	- The AGV should be available near the Operator, ready to receive the picked parts. - The AGV's speed is the average value between its initial, limit, and final speeds. - Multiple AGVs, if present, are synchronized to maintain smooth operations and avoid collisions or congestion. - Potential maintenance requirements and planned downtime for the AGVs to maintain operational efficiency occur outside the cycle time. - The AGV has a limited capacity in weight and volume. **For the AHK System:** - Once the AGV is fully loaded, it moves to the sorting zone for further processing - A new AGV is stationed near the operator to promptly replace the fully loaded AGV and continue the kitting process. **For the Sequential Hybrid Kitting (SHK) System:** - When the kit is completed with the parts allocated to the collaborative area, the AGV leaves the kitting area.
Empty Bin Removal	- In a cycle time, full bins are consumed. - The time for picking empty bins is considered an average value for all types of bins. - The evacuation ramps can be located at the beginning, middle, or at the end of a rack. - The operator doesn't fail at picking empty bins.

Sorting	**For the AHK System:** - The operator can sort multiple parts simultaneously. - The tugger train already has the kit boxes placed and ready to receive parts. - The human operator doesn't fail at picking parts to sort. - The tugger train remains stationary during the positioning of the parts. - The manipulator and operator can work simultaneously.
Packaging removal	- The operator can remove all packaging items. - The Manipulator can fail at picking interlayer sheets and dividers. - No travel time is needed to remove packaging items. - The number of items is defined considering that parts consumed are from full bins.

Table B.1: Assumptions considered for the Collaborative Kitting Area.

Appendix C

Other Kitting Assumptions

Operation	Assumption
Tugger Train	**For the Asynchronous Hybrid Kitting (AHK) System:** - The tugger train is positioned between the robotic and the collaborative kitting areas to receive the kit boxes. - The tugger train can carry and transport multiple kits. - The warehouse can have multiple tugger trains available to allocate to the kitting area. - All the kit boxes can be placed on the tugger train, with appropriate places to place them. - After leaving the kitting area, the tugger train stops at workstations in the Border of Line (BoL) to deliver the kits. - The tugger train is fully operational when allocated to the kitting area in order to deliver kits for the BoL.
Kit Box Preparation	**For the Sequential Hybrid Kitting (SHK) System:** - A human operator, located before the robotic kitting area, prepares the kit boxes in the AGVs. - The AGV can carry and transport one kit. - Empty kit boxes are within reach for the operator, so no travel time is needed to place the kit box. - t_{AGV_kp} includes the time to pick the kit boxes and place them in the correct position in the AGV. - The human operator can make the operation faster picking multiple kit boxes at the same time.

AGVs to deliver kits	**For the SHK System:** - When the kit on the AGV is completed in the collaborative kitting area, the AGV can start the trip to deliver it to the correct workstation in the BoL. - $t_{AGV\_delivery}$ is the average time taken by an AGV to deliver a kit box to the BoL. - The AGVs are fully operational when allocated to transport and deliver kits for the BoL.

Table C.1: Assumptions considered for operations outside the robotic and collaborative kitting areas.

Appendix D

Mathematical demonstration of the distance traveled by the AGV

The following appendix provides a demonstration of how the relationship between the distance traveled by the AGV and the distance traveled by the picker (either being an AMR or a human operator) was derived for the Asynchronous Hybrid Kitting (AHK) System. By using integral theory relations, the following formulation justifies the relationship, considering a statistical approach that aligns with the observed behavior presented in Figure D.1.

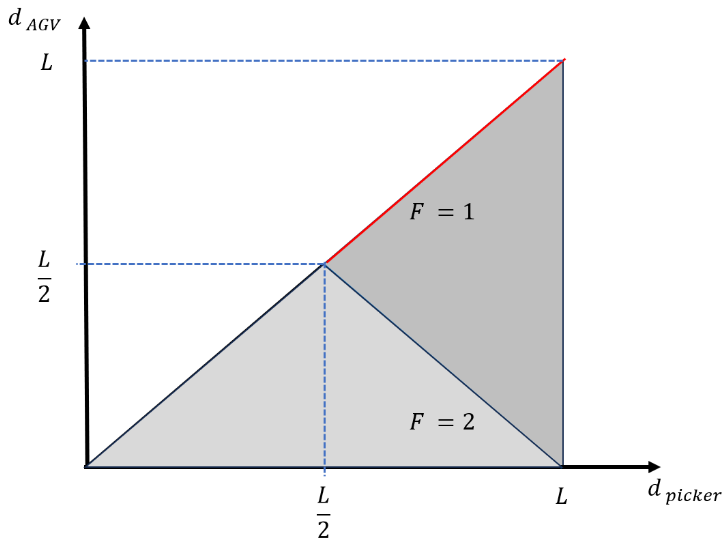

Figure D.1: Graphic representing the relation between the distance traveled by the AGV and the picker (AMR or Human Operator).

Average Value Theorem. *If f is a continuous function on [a,b], then its average value on [a,b] is given by the formula:*

$$f_{\mathrm{AVG}[a,b]} = \frac{1}{b-a} \cdot \int_a^b f(x)dx. \tag{D.1}$$

For the case when $F = 1$ (the picking area has only one facade), we know that $d_{AGV}(d_{picker}) = d_{picker}$. Therefore, we can express the average distance traveled by the AGV as:

$$\begin{aligned}\bar{d}_{AGV} &= \frac{1}{L-0} \cdot \int_0^L d_{AGV}(d_{picker})\, dd_{picker} = \\ &= \frac{1}{L} \cdot \int_0^L d_{picker}\, dd_{picker} = \\ &= \frac{1}{L} \cdot \left.\frac{d_{picker}^2}{2}\right|_0^L = \frac{1}{L} \cdot \left[\frac{L^2}{2} - \frac{0}{2}\right] = \frac{L}{2}_{Q.E.D.}\end{aligned} \tag{D.2}$$

For the case when $F = 2$ (the picking area has two facades), we know that if $d = \frac{L}{2}$, we have $d_{AGV}(d_{picker}) = d_{AGV}(L - d_{picker})$, since the function in symmetric around $\frac{L}{2}$. To prove this, we need to demonstrate:

$$\int_0^L f(x)\, dx = 2 \cdot \int_0^{\frac{L}{2}} f(x)\, dx \tag{D.3}$$

Using the following steps:

$$\begin{aligned}\int_0^L f(x)\, dx = \int_0^{\frac{L}{2}} f(x)\, dx + \int_{\frac{L}{2}}^L f(x)\, dx = \\ &\overset{f(x)=f(L-x)}{=} \int_0^{\frac{L}{2}} f(x)\, dx + \int_{\frac{L}{2}}^L f(L-x)\, dx = \\ &\overset{y=L-x}{=} \int_0^{\frac{L}{2}} f(x)\, dx + \int_{\frac{L}{2}}^0 f(y) \cdot (-1)\, dy = \\ &= \int_0^{\frac{L}{2}} f(x)\, dx + \int_0^{\frac{L}{2}} f(y)\, dy = \\ &= 2 \cdot \int_0^{\frac{L}{2}} f(x)\, dx_{Q.E.D.}\end{aligned} \tag{D.4}$$

In this way, we can determine the average distance traveled by the AGV in a storage area with two facades:

$$\begin{aligned}\bar{d}_{AGV} &= \frac{1}{L} \cdot \int_0^L d_{AGV}(d_{picker})\, dd_{picker} = \\ &= \frac{1}{L} \cdot 2 \cdot \int_0^{\frac{L}{2}} d_{AGV}(d_{picker})\, dd_{picker} = \\ &= \frac{2}{L} \cdot \left.\frac{d_{picker}^2}{2}\right|_0^{\frac{L}{2}} = \frac{2}{L} \cdot \frac{L^2}{2^2 \cdot 2} = \frac{L}{4}_{Q.E.D.}\end{aligned} \tag{D.5}$$

Appendix E

Dataset considered for the models

Table E.1: Dataset considered for the general parameters.

Notation	Description	Value(s)	Units
BS	Number of End Products (EPs) prepared simultaneously	[1, 12]	-
Z	Total number of SKUs	165	-
A	Total area available for the hybrid kitting system	600	m^2

Table E.2: Dataset considered for the components and bin parameters.

Notation	Description	Value(s)	Units
n_i	Average quantity of SKU i in the BOM	[1, 16]	-
f_i	Frequency of usage of SKU i in the EPs	[0.05, 1]	-
BW_i	Storage bin width of SKU i	[0.2, 0.6]	m
P_i	Number of components of SKU i in a complete storage bin	[4, 200]	-
IL_i	Number of interlayer sheets in a complete bin of SKU i	[0, 7]	-
D_i	Number of dividers in a complete bin of SKU i	[0,2]	-
Fo_i	Number of foam protections in a complete bin of SKU i	[0,1]	-
PB_i	Number of plastic bags in a complete bin of SKU i	[0,5]	-
Vol_i	Volume of SKU i	[0.001, 0.026]	m^3
M_i	Weight of SKU i	[0.01, 1]	kg
$feas_i$	Feasibility of SKU i for robotic picking	0 or 1	-

Table E.3: Dataset considered for the robotic kitting area parameters.

Notation	Description	Value(s)	Units
Bg	Percentage of t_{image} occuring in background	50%	-
AW^R	Aisle's width in the robotic kitting area	2	m
RD^R	Storage Rack's depth in the robotic kitting area	1	m
S^R	Horizontal spacing between two successive bins	0.1	m
RL^R	Standard rack Length in the robotic kitting area	1.6	m
N^R_{levels}	Storage racks levels in the robotic kitting area	2	-
F^R	Number of facades in the robotic kitting area	2	-
Ps^R	Picking sides in the robotic kitting area	1	-
AMR	Number of AMRs working in the robotic kitting area	[1,5]	-
v_{AMR}	AMRs average velocity	0.6	m/s
v_{AGV}	AGVs average velocity	0.8	m/s
$Sort^R$	Distance in the sorting zone traveled by the AGV	1	m
t^R_i	SKU i picking time by the AMR/fixed manipulator	[4, 7]	s
t_{image}	Average time for the AMR/fixed manipulator to capture and process a single image	2	s
t^R_{bin}	Average time for the AMR to pick an empty bin and dispose it in the evacuation zone	5	s
t^R_s	Average time for the fixed manipulator to pick a part from the AGV to the kit box	3	s
t^R_{IL}	Average time for the AMR to remove an interlayer sheet from a bin	7	s
t^R_D	Average time for the AMR to remove a divider from a bin	6	s
$t_{gripper\_parts}$	Average time for the AMR to change the gripper to pick different parts	3	s
$t_{gripper\_pack}$	Average time for the AMR to change the gripper to pick packaging items	3	s
$t_{gripper\_bin}$	Average time for the AMR to change the gripper to pick empty bins	3	s
Cal	Additional proportion of time needed for gripper calibration	1%	-
PE_i	Probability of occurring a picking error during the initial attempt of picking SKU i	1, 2, 5,..., 50%	-
PE_{bin}	Probability of occurring a picking error of empty bins	1, 2, 5,..., 50%	-

PE_{sort}	Probability of occurring a picking error sorting parts	1, 2, 5,..., 50%	-
$PE_{interlayer}$	Probability of occurring a picking error of interlayer sheets	1, 2, 5,..., 50%	-
$PE_{divider}$	Probability of occurring a picking error of bin dividers	1, 2, 5,..., 50%	-
Col	Impact on collaborating with a human operator on completing kits	1, 2, 5,..., 50%	-
AR_{parts}	Parameter describing an efficient assignment rule for changing the gripper to pick a different part	90%	-
AR_{pack}	Parameter describing an efficient assignment rule for changing the gripper to pick a different packaging item	90%	-
AR_{bins}	Parameter describing an efficient assignment rule for changing the gripper to pick a bin	90%	-

Table E.4: Dataset considered for the collaborative kitting area parameters.

Notation	Description	Value(s)	Units
Ef_{kit_prep}	Parameter describing the efficiency in preparing kit boxes	10%	-
AW^C	Aisle's width in the collaborative kitting area	2	m
RD^C	Storage Rack's depth in the collaborative kitting area	1	m
S^C	Horizontal spacing between two successive bins	0.1	m
RL^C	Standard rack Length in the collaborative kitting area	1.2	m
N^C_{levels}	Number of levels in the storage racks in the collaborative kitting area	4	-
F^C	Number of facades in the Collaborative kitting area	2	-
Ps^C	Picking sides in the collaborative kitting area	1	-
OP	Number of operators working in the collaborative kitting area	[1,5]	-
$\bar{v}_{OP}$	Human operators average velocity	0.5	m/s
$\bar{v}_{AGV}$	AGVs average velocity	0.8	m/s
$Sort^C$	Distance in the sorting zone traveled by the AGV	1	m
sim_i	Number components of SKU i that a human operator can pick simultaneously	[1, 6]	-

sim_{pack}	Number of packaging items that an operator can pick simultaneously	2	-
t_{kp}	Average time for the operator to prepare a single kit box	3	s
t_{p2l}	Average time required for the pick-to-light system to send data packages to the modules	0.052	s
t_{obs}	Average time required for the operator to locate and identify a single pick-to-light module turned on	1	s
t_i^C	Time for the operator to pick SKU i	[2,5]	s
t_{bin}^C	Average time for the operator to pick an empty bin and dispose of it in the evacuation zone	2.5	s
t_s^C	Average time for the operator to pick a part from the AGV to the kit box	3	s
t_{IL}^C	Average time for the operator to remove an interlayer sheet from a bin	2	s
t_D^C	Average time for the operator to remove a divider from a bin	2	s
t_F	Average time for the operator to remove a foam protection from a bin	2	s
t_{PB}	Average time for the operator to remove a plastic bag from a bin	4	s
EC_{com}	Error correction factor related to additional data packages resent	2.5%	-
EC_{obs}	Error correction factor related to operator failing to observe a turned-on module	5%	-
EC_{detect}	Error correction factor related to pick-to-light module proximity sensor failure, leading to the module's light being turned off incorrectly	1%	-
EC_{sort}	Error correction factor related to the operator rectifying any mistakes by picking a wrongly placed part from one kit box and relocating it to the correct kit box;	1%	-

Table E.5: Dataset considered for the tugger train.

Notation	Description	Value(s)	Units
$TUGGER$	Tugger trains available	2	-
T_{run}	Tugger train's displacement time	1200	s
t_{stop}	Tugger train's single stopping time	10	s
N_{kits_MAX}	Tugger train kit capacity	16	-

Table E.6: Dataset considered for technical parameters.

Notation	Description	Value(s)	Units
M_{AGV}	AGV's maximum weight capacity	500	kg
Vol_{AGV}	AGV's maximum volume capacity	0.28	m^3
M_{kit}	Kit box's maximum weight capacity	20	kg
Vol_{kit}	Kit box's maximum volume capacity	0.048	m^3
t_{AGV_kp}	Average time required to prepare a kit box into the AGV	2	s
$t_{AGV\_delivery}$	Average time required for the AGV to deliver a kit on the Border of Line (BoL)	300	s