Data-driven analysis of idle time in a Goods-to-Person system: Insights from an automated warehouse case study

Laura Amodeo*‡, Nhan Quy Nguyen*†, Yassine Ouazene*†, Farouk Yalaoui*†,
Fabien Cordon‡, Murat Kurban‡, Jerôme Lansoy‡
* Computer Sciences and Digital Society Laboratory (LIST3N),
Université de Technologie de Troyes, 12 rue Marie Curie, CS 42060, 10004, Troyes, France
Emails: {laura.amodeo, nhan_quy.nguyen, yassine.ouazene, farouk.yalaoui}@utt.fr
† Chaire Connected Innovation,
Université de Technologie de Troyes, 12 rue Marie Curie, CS 42060, 10004, Troyes, France
‡ Lacoste,
Rue de la Forêt, 10800 Buchères, France
Emails: {fcordon, mkurban, jlansoy}@lacoste.com

Abstract—The textile industry has witnessed remarkable growth, largely driven by the expansion of e-commerce. To meet the increasing demand for faster order fulfillment, warehouses are adopting advanced automation technologies. This study focuses on the idle time analysis within a goods-to-person order picking system in an automated warehouse. As a first step, a cause-and-effect tree is developed to systematically identify potential factors that contribute to idle time. Subsequently, the most significant indicators are determined through a mathematical model based on the Least Squares Principle. This approach prioritizes the indicators that have the most impact, enabling a targeted analysis of the root causes of idle time and providing valuable insights to improve system efficiency.

Index Terms—Automated warehouse, Goods-to-person system, performance evaluation, idle time, root cause analysis, data analysis

I. Introduction

Recent growth in e-commerce has driven the demand for more efficient warehouse operations. Customers now expect faster delivery times, forcing warehouses to accelerate their processes to meet these expectations. As a result, advanced systems are needed to handle high-order volumes efficiently.

Warehouses are evolving into *smart warehouses* through automation technologies such as robotic picking systems, autonomous guided vehicles (AGVs), and automated storage and retrieval systems (AS/RS). Order-picking systems have also undergone significant advancements, with technologies such as Goods-to-Person (GTP) systems, automated picking robots (e.g., Kiva system) and intelligent sorting solutions becoming increasingly common. The primary goal of these technologies is to improve storage capacity, accelerate order fulfillment, and facilitate operators' tasks. With these improvements, warehouses can now process an ever-growing number of orders each day.

Human-robot collaboration is widely adopted to assist warehouse workers and boost productivity. Winkelhaus et al. [9] categorize order-picking systems into two main types: *parts-to-picker* and *picker-to-parts*. In a parts-to-picker system, automated storage units or robots transport items to the workstation, significantly reducing workers' travel time within the warehouse.

The GTP workstation is an automated order-picking solution that uses conveyor systems to deliver items directly to operators. By eliminating the need for operators to walk to retrieve items, this setup reduces physical effort, increases efficiency, and minimizes errors. The items are automatically transported to the operator's workstation, allowing them to focus solely on selecting the correct products for order fulfillment. This system is particularly prevalent in e-commerce warehouses, where order volume and item variety fluctuate significantly.

Despite its efficiency, the GTP system can experience idle time issues, especially during periods of high demand. Bottlenecks on the conveyors can delay the delivery of items to the workstations, leaving operators temporarily without tasks. Idle time refers to these periods when operators are unable to work because the system does not provide them with tasks in a timely manner.

The remainder of this paper is structured as follows. Section 2 provides a comprehensive review of the literature on order-picking systems and their optimization techniques. Section 3 introduces the operational flows of a smart warehouse and defines the problem under investigation. Section 4 presents a methodology for identifying key indicators that contribute to idle time, including a systematic analysis of potential causes and their correlations. This section also details the mathematical approach used to determine the most influential factors. Section 5 discusses computational results derived from the mathematical model, highlighting critical indicators that significantly impact idle time. Finally, Section 6 concludes the study and outlines potential future research directions.

II. LITERATURE REVIEW

Smart warehouses have been introduced into logistics to address the increasing demand with faster and more efficient operations. This subject has been explored by Zhen and Li [12] and detail technical advances in the field of information interconnection, equipment automation, and environmental sustainability. The introduction of smart warehouses has revolutionized every step of the package delivery process to customers. Rapid advancement in technology has significantly changed the way order-picking systems operate, leading to more efficient and flexible solutions. As these technologies have been integrated into warehouse management, order picking systems have evolved to better meet demands. Pinto et al. [11] present all types of system from automated solutions to human-robot collaboration. The performance of the system is a critical indicator for measuring the efficiency of a warehouse. It can be evaluated using various metrics: productivity, tardiness, operator's well being. First, the performance of two parts-to-picker systems: Miniload and Kiva system is analyzed by Bozer and Aldarondo [1] and highlights the advantages of both systems. The performance of order picking is also studied by Mizraei et al. [6] in examining the influence of storage allocation on warehouse efficiency. On the other hand, Tappia et al. [10] explore the relationship between storage technologies and the performance of order picking in warehouse in terms of efficiency and costs. Synchronization of the system to ensure seamless operations significantly impacts overall performance. Boysen et al. [7] propose a coordination between storage and picking processes to minimize replenishment delays and optimize the efficiency of the system. Kumar et al. [8] investigate the performance of the system in interest of the picker's well-being. Optimization of the order-picking system involves improving several key elements, including order batching, order sequencing, and storage allocation [5]. Research can focus either on the order-picking system, exploring the methods and technologies used to optimize order fulfillment, or on the warehousing system, studying the efficiency of inventory allocation, retrieval and management. Lenoble et al. [4] focus specifically on the Vertical Lift Module (VLM), a type of storage equipment, and optimizes the completion time of the storage system with order batching. The travel time between the storage zone and the workstation is a critical factor influencing the performance of an order-picking system. Research can lead to a study of crane travel that transports bins to workstations [3] or robot travel time [2]. The thesis of Vacher [13] examines another dimension of performance by focusing on optimization of the box scheduling on conveyors leading to GTP workstations. All these articles seek to optimize the performance of a picking system by optimizing certain parameters or flows. Our study will not focus specifically on system performance, but on the issues that prevent optimum performance from being achieved: in this case, we'll talk about idle time. This adds a new dimension to optimizing the performance of automated systems. Our study will therefore focus on the causes of idle time in this type of system. In fact, although this system is very efficient, since it can process a large number of orders per day, it can encounter difficulties. To illustrate our contribution, we summarize the findings in Table I, which provides an overview of various studies on order picking systems. The table highlights key aspects, such as the types of storage system and handling operations examined in previous research. This categorization facilitates a comparative analysis of the characteristics of the warehouse described in the literature and those of our study.

III. PROBLEM DESCRIPTION

A. Warehouse description

The paper studies an automated warehouse that prepares orders for the textile industry. The flow starts with the arrival of the finished products which are then stored on the basis of the box size. The boxes must respect the requirements of the Miniload system. This AS/RS is designed to handle small loads such as cartons, bins, or trays. It uses shuttles to store and retrieve items with horizontal and vertical movements. A Miniload system is highly effective in processing a large volume of boxes in a short time, making it an ideal solution for high-demand warehouse operations. In case not, the boxes are stored manually in other shelves. When required, they are transferred to the picking zone for order fulfillment using conveyors. Picking operators prepare orders by receiving the required products at their workstation and fulfilling them with the specified quantities. The picking system will be more detailed in the following subsection. The flow then splits into two streams : B2B and B2C. Orders in the B2B streams can pass through the personalization zone. Depending on store demand, operators may apply price tags, theft protection devices, or RFID tags to the products. Finally, the products are packed and shipped to the store for delivery. The B2C stream is different; all the client demands arrive in the zone mixed up in boxes. The operator retrieves the carton and assembles the products to complete the order. The packing process is also carried out at the same workstation, ensuring that the order is properly secured. Once completed, the package is ready for dispatch. After mapping the entire warehouse flow in Fig. 1, our study focuses on the picking process, where all products are routed to be prepared for final orders. It also represents a bottleneck in the warehouse and any issues in this zone can significantly impact the entire process.
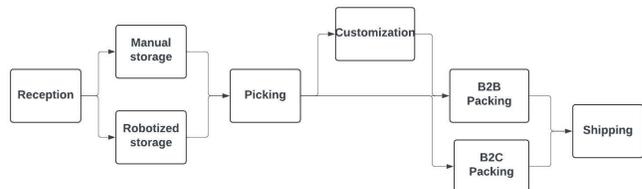

Fig. 1. Warehouse flow

TABLE I
RESEARCH POSITIONING

Reference	Picking Zone	Handling Operation	Data-Driven Analysis	Optimization Objective
Boysen et al. (2017)	Single	Multi	None	Minimize total robot travel time
Bozer et al. (2018)	Multi	Multi	Simulation-based analysis	Minimize retrieval time
Lenoble et al. (2018)	Multi	Single	None	Minimize total order processing time
Füßler et al. (2019)	Single	Multi	Discrete event simulation	Maximize throughput and minimize processing time
Tappia et al. (2019)	Single	Multi	Performance modeling and simulation analysis	Minimize operational cost and maximize performance
Vacher et al. (2020), Mirzaei et al. (2021), Srinivas et al. (2022)	Single	Multi	Simulation-based analysis	Minimize total order-picking time
Boysen et al. (2023)	Multi	Multi	None	Review of synchronization problem
Kumar et al. (2023)	Multi	Multi	Impact of perceived workload	Maximize system performance and minimize workload
Our paper	Multi	Multi	Cause-and-effect tree, mathematical model	Minimize idle time

B. Picking zone

The picking zone is entirely automated and is divided into two distinct sectors: storage and preparation. The storage is a Shuttle Based Storage and Retrieval System (SBS/RS) and follows the same feature of an AS/RS. An autonomous shuttle delivers the products to the vertical lift using only horizontal movements. This system strategically stores the most requested products at the front of the storage. This organization reduces retrieval times for high-demand products, improving the overall performance of the system. These shuttles are distributed across different levels and aisles, optimizing the flow and organization of goods within the automated system. The vertical lift ensures the connection between the storage zone and the preparation. The box exits the Miniload when a demand is formulated and travels directly to the SBS/RS. Then it is delivered to the correct workstation via a conveyor system. The box enters the GTP system, which consists of two areas: a buffer zone and a picking zone. The buffer zone sequences the boxes in the right order and temporarily holds it until needed. The conveyor transports the box to the picker, who then fulfills the order following the instructions displayed on the tablet. The package reaches the workstation when all the required items are prepared and ready to be shipped. If necessary, it can be prepared on different workstations when the product cannot reach the workstation on time. The package is then prepared at another station or waits for the right product to re-circulate in the system, potentially creating saturation. Fig. 2 shows the complexity of the picking system between the storage allocation and distribution to the GTP stations. Inbound and outbound flows must be organized to arrive simultaneously at the station. This organization must account for upstream flows, potential bottlenecks, and other challenges to ensure total system performance. This introduces the idle time that may occur at each GTP within the zone. Issues such as product delivery, equipment malfunctions, and conveyor saturation can cause periods when operators are unable to perform their tasks. The idle time represents a significant part of an operator's work by causing fragmented work and interrupted tasks. Reducing idle time will increase picking productivity and maintain a steady workflow. This improves operator performance while also maximizing overall warehouse productivity. The following parts of the paper concentrate on the methodology for optimizing the idle time of the GTP system. This includes the data analysis used to identify the indicators that influence idle time and the presentation of the mathematical model developed to quantify their impact.
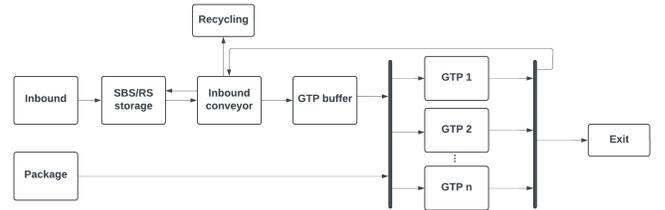

Fig. 2. Picking zone

IV. METHODOLOGY

The idle time in the order picking system is an important issue that significantly impacts productivity. The objective is to minimize the idle time present in the order-picking system by targeting actions on the most important indicators. An indicator in a GTP system refers to an observable phenomenon that can be monitored over time through data collection. Our study aims to identify the root causes of idle time in a GTP system from the available indicators and quantify the impact of each of them. By reducing the most contributing indicators, we intend to improve idle time. The objective of this section is to collect the data and analyze the indicators that contribute to idle time in a GTP system. This involves following their evolution over time and determining which indicators affect the most overall productivity. First, the method focuses on identifying indicators that can impact idle time at workstations through observation sessions. These indicators are analyzed over time to evaluate their influence on idle time, enabling the

formulation of potential hypotheses regarding their correlations and effects. To validate these assumptions, we develop a mathematical model to quantify the influence of each indicator and a correlation heatmap to find the relationship between them. This allows us to prioritize the most impactful ones, directing the focus of further analysis and optimization efforts.

A. Data collection

Observation sessions and discussions with operators are essential for a complete understanding of how the entire system operates. It will help us formulate initial assumptions on the root causes of idle time. This shows that the system can be affected by the upstream flow. In fact, if the warehouse reception is saturated, no boxes will be processed in the system. Other assumptions can be made regarding the maintenance of the system. For example, interruptions caused by equipment malfunctions or unplanned defaults can lead to idle time. Consultations with experts offer more advanced possibilities for more internal and technical issues. For analysis, daily data extracts are available to have an overview of the system performance in terms of saturation, pick-up index, productivity, etc. All of these data are translated by time and GTP, and are used by various experts in the picking zone. These data enable them to make decisions throughout the day and alert them to system problems. Discussions with experts have enabled us to focus our study on various indicators that they believe have an impact on idle time.

B. Data analysis

After collecting the data in the previous section, we are now able to analyze it over several months, considering different demand states. This analysis will allow us to examine how variations in the system affect idle time and other key performance indicators. This leads us to observe different performance patterns, especially weekends, and the positioning of workstations. For example, weekends show a distinct behavior, with idle time often being higher due to reduced demand or fewer operational activities. This approach allows identifying all potential factors of idle time. We study the graphical behavior of indicators over time to observe a correlation with idle time. The next step is to classify the indicators to determine root causes and better understand the system.

C. Modeling

We gather all the issues noticed and formulate them into a cause-and-effect tree (Fig. 3). The tree highlights the root causes of the problem and helps us to have an overview of the system. Figure 3 shows five root causes for idle time: conveyor saturation, time out, mechanical default, packages, and inbound boxes. Time-out is defined by a time lapse in which the right box does not arrive on time to the workstation. After four minutes of waiting, the system delivers the next box. The research also evaluates the number of inbound boxes and packages in the station to evaluate the availability of the system to meet demand. The next step involves using a mathematical model to identify the most influential indicators contributing to idle time. The model helps prioritize these indicators, enabling targeted improvement strategies.
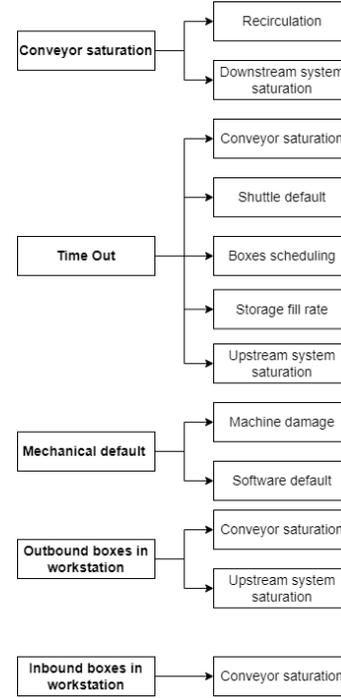

Fig. 3. Cause-and-effect tree of idle time

D. Impact evaluation

After finding all the indicators, the next steps are to find the most involved in the idle time to narrow the research. This section introduces a mathematical approach using the least-squares method to verify the correlation of indicators with idle time and the design of a correlation heatmap. The objective is to intensify the research on crucial indicators to optimize idle time. This model minimizes the sum of squared differences between the observed idle time values and the linear combination of indicators. This approach allows evaluating multiple indicators simultaneously and quantifying the degree of correlation.

Parameters

- i : number of indicators
- k : number of periods
- x_{ik} : measurable indicator i at period k
- I_k : idle time at period k

Decision variables

- λ_i : factor of correlation of indicators

Objective function

$$min \sum_k (I_k - \phi(k))^2 \tag{1}$$

with

$$\phi(k) = \sum_{i=1}^{I} x_{ik} * \lambda_i \qquad (2)$$

Constraint

$$\sum_i \lambda_i = 1 \qquad (3)$$

We define the linear function $\phi(k)$ as a linear combination of indicators. Each indicator is assigned a factor of correlation λ_i. It will provide a simplified interpretation of results. The objective of the model is to calculate the correlation between the indicators and the idle time by using the least squares principle (1). The purpose of the model is to penalize the derivation between the idle time and the linear combination $\phi(k)$.To ensure that the model remains balanced, we introduce a constraint: the sum of the factors must be equal to 1. This normalizes the contribution of the indicators, maintaining a proportional relationship.

By implementing this model, we aim to quantify the contribution of each indicator and validate their impact through computational analysis. We continue the impact evaluation with a correlation heatmap that will help visually represent the relationship between variables. This will give two types of data: the coefficient of contribution of idle time (mathematical model) and the strength of relationship between indicators (correlation heatmap).

V. RESULTS

A. Computational process

After collecting the indicators through observation sessions and discussions with operators and experts, we are able to confront ten indicators for idle time, each of them contributing to different steps of the GTP system. We collect indicator data for several months, allowing us to observe different types of work and demand. This analysis reveals specific variations in demand patterns, with notable fluctuations occurring during the weekends. Weekend production is specific: lower demand, fewer working hours. The idle time seems to be more present in this period. This means that the behavior of the inactivity time differs according to the day of the week and therefore implies that the improvement is different for weekdays and weekends. We choose therefore to direct our study from two perspectives: with and without weekends, acknowledging the distinct demand patterns observed during these periods. This leads us to conduct the analysis on $k = 112$ operational periods, including weekends and $k = 89$ periods without weekends, which represents four months of record. The compilation is done in LINGO systems and the results are expressed in Tables II and III.

The next phase of the study examines the correlations between the identified indicators to understand their influence on each other through a correlation heatmap (Fig.4).

B. Discussions

This section focuses on evaluating the influence of selected indicators on idle time using the proposed mathematical model. The first table reveals four indicators most closely correlated with idle time: package recirculation, storage filling, Time-Out, and pickup index. Package recirculation, where a box must be prepared at multiple stations, can cause system saturation. This process delays the timely arrival of packages to their designated workstations, contributing to inefficiencies. Time-out is closely related to idle time, as delays in the arrival of boxes significantly impact workstation activity. The storage system's filling process contributes to idle time, as boxes stored further back in the system require more time for shuttles to retrieve them. Finally, the pickup index refers to the number of products that must be picked up from the box to meet the order requirements. The higher it is, the more difficult it is for the machine to deliver the product to the station on time. The results reveal that the first three indicators collectively contribute to more than 80% of the observed idle time in the system. This finding underscores their critical importance in optimizing the performance of the system. The table III highlights additional indicators strongly correlated with idle time: package recirculation, Time-Out, number of available workstations. This observation demonstrates that correlation with idle time varies significantly depending on the part of the week, with specific patterns emerging during weekends and weekdays.

Next, the correlation heatmap highlights the correlation between idle time and other indicators, and its results align closely with the computational findings (package recirculation, Time Out). This also reveals that these indicators are linked to mechanical failures or the number of tasks assigned to operators to meet demand. Our research focuses on package recirculation, concentrating on the most correlated indicators to efficiently optimize idle time.

TABLE II
COMPUTATIONAL RESULTS OF THE MATHEMATICAL MODEL (WITH
WEEKENDS)

i	λ_i	Results
1	Conveyor Saturation	0.0000
2	Time-out	**0.1721**
3	Mechanical failure	0.0000
4	Storage filling	**0.2267**
5	Pickup index	**0.1604**
6	Number of multi reference in box	0.0000
7	Number of available workstation	0.0015
8	Number of tasks	0.0000
9	Number of inbound boxes per workstation	0.0115
10	Package recirculation	**0.4277**

VI. CONCLUSION

Warehouses have become increasingly automated, integrating advanced systems to improve efficiency and productivity. The objective of smart warehouses has evolved to prioritize improving operator working conditions along with enhancing efficiency. The picking zone has seen significant technical

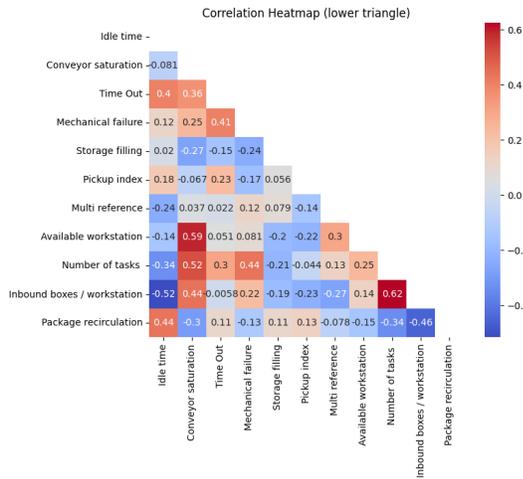| i	λ_i	Results
1	Conveyor Saturation	0.0000
2	Time-out	**0.3255**
3	Mechanical failure	0.0000
4	Storage filling	0.0782
5	Pickup index	0.0045
6	Number of multi reference in box	0.0000
7	Number of available workstation	**0.1524**
8	Number of tasks	0.0000
9	Number of inbound boxes per workstation	0.0000
10	Package recirculation	**0.4393**

Fig. 4. Correlation heatmap

advances designed to improve productivity using technologies that reduce operator travel and manual handling. Moreover, this system handles high complexity and seems to represent and seems to be a disadvantage for optimal performance. This paper studies the idle time of the GTP system as a new way to improve warehouse performance. This leads to analysis of the root cause of the problem by constructing a cause-and-effect tree thanks to observation sessions. This method systematically identifies the indicators that contribute to idle time, providing a clear understanding of the underlying problem. To address this, we employ a mathematical model based on the Least Squares method to pinpoint the most influential factors. By analyzing the relationship between observed idle time and key operational indicators, this approach ensures a comprehensive data-driven investigation of root causes. The strength of this proposal lies in the fact that the method can be used for all types of industry using a GTP system and recording idle time.

The analysis reveals that idle time is primarily caused by package recirculation, indicating system saturation and an inability to efficiently deliver products to the workstation. This issue is closely linked to the second identified factor: time-out, where products do not arrive at the workstation on time. These findings direct the study toward the evaluation of the product planning process, focusing on the timing and coordination of

production launches. The next steps of the analysis will focus on the most important indicators: package recirculation. The main objective is to analyze the first stage of the package process, focusing on the production launches. This means first understanding the methods currently in use and then proposing an optimization. Focusing on the first step allows us to control the beginning of the flow and thus to focus on the next steps, specifically on the distribution of boxes to workstations.

REFERENCES

[1] Y. Bozer and F. Aldarondo, "A simulation-based comparison of two goods-to-person order picking systems in an online retail setting," International Journal of Production Research, vol. 56, 2018, pp. 3838–3858.

[2] N. Boysen, D. Briskorn, and S. Emde, "Parts-to-picker based order processing in a rack-moving mobile robots environment," European Journal of Operational Research, vol. 262, 2017, pp.550–562.

[3] D.Füßler and N. Boysen, "High-performance order processing in picking workstations,"Journal on Transportation and Logistics, vol. 8, 2019, pp. 65–90.

[4] N. Lenoble, Y. Frein and R. Hammami, "Order batching in an automated warehouse with several vertical lift modules: Optimization and experiments with real data," European Journal of Operational Research, vol. 267, 2018, pp.958–976.

[5] S. Srivinas and S. Yu, "Collaborative order picking with multiple pickers and robots: Integrated approach for order batching, sequencing and picker-robot routing," International Journal of Production Economics, vol. 254, 2022.

[6] M. Mirzaei, N. Zaerpour and R. de Koster, "The impact of integrated cluster-based storage allocation on parts-to-picker warehouse performance," Transportation Research Part E: Logistics and Transportation Review, vol. 146,2021.

[7] N. Boysen, S. Schwerdfeger and K. Stephan,"A review of synchronization problems in parts-to-picker warehouses,"European Journal of Operational Research, vol. 307, 2023, pp. 1374–1390.

[8] S. Kumar, J-B. Sheu and T. Kundu,"Planning a parts-to-picker order picking system with consideration of the impact of perceived workload,"Transportation Research Part E: Logistics and Transportation Review, vol. 173, 2023.

[9] S. Winkelhaus, E.H. Grosse and S. Morana,"Towards a conceptualisation of Order Picking 4.0,"Computers & Industrial Engineering, vol. 159, 2021.

[10] E. Tappia, D. Roy, M. Melacini and R. de Koster,"Integrated storage-order picking systems: Technology, performance models, and design insights,"European Journal of Operational Research, vol. 274, 2019, pp.947–965.

[11] A. R. F. Pinto, M.S. Nagano and E. Boz, "A classification approach to order picking systems and policies: Integrating automation and optimization for future research,"Results in Control and Optimization, vol. 12, 2019.

[12] L. Zhen and H. Li, "A literature review of smart warehouse operations management,"Frontiers of Engineering Management, vol. 9, 2022, pp.31–55.

[13] B. Vacher, "Techniques d'optimisation appliquées au pilotage de la solution GTP X-PTS pour la préparation de commandes intégrant un ASRS," 2020, pp.207.