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PAWEŁ RYMARCZYK
Netrix S.A., Poland
ORCID iD: orcid.org/0000-0002-5990-4771

SYLWESTER BOGACKI
WSEI University in Lublin, Poland
ORCID iD: orcid.org/0000-0002-8330-4573

CEZARY FIGURA
WSEI University in Lublin, Poland
ORCID iD: orcid.org/0009-0003-4756-7354

MAREK RUTKOWSKI
WSEI University in Lublin, Poland
ORCID iD: orcid.org/0009-0009-5910-7893

PIOTR STALIŃSKI
Graduate School of Business - National-Louis University, Poland
ORCID iD: orcid.org/0000-0002-1388-8999

OPTIMIZING ORDER PICKING PROCESSES IN WAREHOUSES: STRATEGIES FOR EFFICIENT ROUTING AND CLUSTERING

OPTYMALIZACJA PROCESÓW KOMPLETACJI ZAMÓWIEŃ W MAGAZYNACH: STRATEGIE EFEKTYWNEGO WYZNACZANIA TRAS I KLASTROWANIA

Abstract

Purpose: The objective of the study was to enhance warehouse productivity by optimizing the routes for order picking and conducting an analysis to determine and establish the shortest possible route in the order picking process, taking into account the tools used, the warehouse layout, and the distribution of products within it.

Methods: The study employed a simulation based on a detailed dataset containing over 307,046 unique order identifiers and 1,050 unique product identifiers. This dataset included information such as order placement dates, product codes, quantities, and precise locations within the warehouse, including coordinates. The simulation modeled the order-picking route using the Single-Picker Routing Problem (SPRP) algorithms to minimize distance and travel time. The methods compared various wave-picking strategies and grouping methods (single-line and multi-line) for their effectiveness.

Results: The applied method significantly reduced the travel distance required by the order picker in the warehouse. The key to this optimization was consolidating orders into waves of specific sizes, achieving a fourfold distance reduction for the studied dataset. Additionally, the solution proposed grouping products by location within the warehouse, either in a single aisle or across multiple aisles based on proximity. Although this method often enhances efficiency, it did not in this particular case. However, it was included as it may yield better results with different datasets and further reduce travel distances in the warehouse.

Discussion: The research underscored the critical role of efficient routing and grouping strategies in warehouse operations. Although wave picking significantly reduced travel distances, the effectiveness of clustering strategies depended on the characteristics of the specific dataset, suggesting the need for tailored solutions based on the warehouse layout and the features of the orders. Future research could extend to integrating product volume and weight variations, which may further optimize order-picking strategies.

Streszczenie

Cel: Celem przeprowadzonych badań była poprawa produktywności magazynu poprzez optymalizację tras kompletacji zamówień oraz przeprowadzenie analizy mającej na celu określenie i wyznaczenie najkrótszej możliwej trasy w procesie kompletacji, biorąc pod uwagę wykorzystywane narzędzia oraz mapę magazynu wraz z rozmieszczeniem produktów.

Metody: W badaniu zastosowano symulację opartą na szczegółowym zestawie danych, który zawierał ponad 307 046 unikalnych identyfikatorów zamówień i 1 050 unikalnych identyfikatorów produktów. Dane te obejmowały informacje takie jak daty składania zamówień, kody produktów, ilości i precyzyjne lokalizacje w magazynie, w tym współrzędne. Symulacja modelowała trasę zbierania zamówień, korzystając z algorytmów problemu marszruty pojedynczego zbieracza (SPRP), aby zminimalizować dystans i czas podróży. Zastosowane metody porównały różne strategie zbierania falowego oraz grupowania (jednoliniowego i wieloliniowego) pod kątem ich efektywności.

Wyniki: Zastosowana metoda znacznie zmniejszyła dystans, jaki musiał pokonać zbieracz zamówień w magazynie. Kluczowym elementem optymalizacji było konsolidowanie zamówień w fale o wybranych rozmiarach, co pozwoliło osiągnąć około czterokrotne zmniejszenie dystansu dla badanego zbioru danych. Ponadto proponowane rozwiązanie obejmowało grupowanie produktów według ich lokalizacji w magazynie, zarówno w pojedynczym korytarzu, jak i między wieloma korytarzami, w zależności od bliskości odległości do pokonania między komórkami. Chociaż ta metoda często poprawia efektywność, w tym konkretnym przypadku tak się nie stało. Została jednak uwzględniona, ponieważ może przynieść lepsze rezultaty w przypadku innych zbiorów danych i dalej zmniejszyć potrzebny dystans do pokonania w magazynie.

Omówienie: Przeprowadzone badanie podkreśliło kluczową rolę efektywnego trasowania i strategii grupowania w operacjach magazynowych. Chociaż zbieranie falowe znacząco zmniejszyło odległości podróży, efektywność strategii klastrowania zależała od charakterystyk konkretnego zestawu danych, sugerując potrzebę dostosowywania rozwiązań na podstawie układu magazynu i cech zamówień. W przyszłości możliwe jest rozszerzenie badań o integrację różnic w objętości i wadze produktów, co może dodatkowo optymalizować strategie zbierania zamówień.

Keywords: *Warehouse Optimization, Order Picking Process, Wave Picking, single-line clustering, multi-line – grouping*

Słowa kluczowe: *Optymalizacja magazynu, Proces kompletacji zamówień, Kompletacja falowa, grupowanie jednoliniowe, grupowanie wieloliniowe*

Introduction

In the current era, as the e-commerce market expands at a dizzying pace and customers demand swift and precise service, optimizing order fulfillment processes in warehouses becomes crucial for operational efficiency and customer satisfaction. The order fulfillment process, also known as *picking,* involves selecting and collecting specific products from the warehouse in response to individual customer orders. Optimizing this process necessitates meticulous analysis and continuous improvement of work methods, technologies, and strategies for managing warehouse space (Dmowski, Wołowiec, Laskowski, Laskowska, 2023).

Contemporary approaches to optimizing order fulfillment leverage advanced information systems and automation, which facilitate faster and more precise inventory management and picking processes (Kembro et al., 2018). The use of predictive demand algorithms and automated storage and retrieval systems (AS/RS) significantly enhances the operational efficiency of warehouses. These systems support dynamic planning and resource reallocation, which are essential in an e-commerce environment where order fulfillment time is a critical performance metric (Boysen et al., 2019).

Beyond the deployment of technology, the proper organization of warehouse space plays a pivotal role in enhancing order-picking efficiency and reducing the time required for product retrieval. The warehouse layout directly influences the ease and speed with which staff can access items, impacting key performance indicators such as total order cycle time and accuracy. Well-designed warehouse layouts streamline the path pickers must take to complete their orders, which not only speeds up processing but also minimizes physical strain and error rates (Roodbergen et al., 2015). This optimization involves detailed planning of aisle widths, shelf heights, and the positioning of high-demand items in easily accessible locations. Recent research underscores the significance of optimizing warehouse layout, including the strategic placement of aisles and picking zones, as a means to shorten order fulfillment durations significantly (Zhang Khan, 2017). Optimizing warehouse layout involves meticulous planning of the physical space to accommodate both existing and anticipated inventory needs, ensuring that items are accessible and storage space is utilized efficiently. Studies highlight the use of simulation models and layout optimization algorithms to determine the most effective arrangement of warehouse components to streamline operations and minimize retrieval times(Dotoli et al., 2015)This approach not only helps improve the physical flow of items but also supports advanced picking strategies like zone picking and batch picking, which further enhance productivity.

The evolution of consumer behavior and technological advancements influence specific order-picking strategies in warehouses and intersect with complex logistical challenges such as the Traveling Salesman Problem (TSP), often referred to in logistics as the picker routing problem. In the context of warehouse optimization, the TSP becomes a critical issue. The TSP involves determining the most efficient route that a warehouse picker must follow to retrieve items from various locations in the warehouse, ensuring the shortest possible travel distance or time. This challenge is exacerbated in the dynamic environment of e-commerce warehouses where rapid and accurate order fulfillment is essential (Yousefikhoshbakht, 2021).

Applying TSP in warehouse settings involves optimizing the path pickers take to minimize the travel distance across all picked items. This optimization not only reduces labor costs but also enhances the speed and accuracy of the picking process, which is crucial in maintaining customer satisfaction in fast-paced e-commerce operations (Bock Boysen, 2023). However, traditional solutions to TSP may not be directly applicable in complex warehouse environments that require handling varied item sizes, multiple picking zones, and fluctuating demand patterns.

Single-order, batch, and wave picking are among the strategies scrutinized for their effectiveness and efficiency in various warehouse settings. Single-order picking, although straightforward, often results in higher travel times and lower overall efficiency, especially in e-commerce environments where orders are characterized by small sizes but high transaction volumes. This inefficiency is further exacerbated in warehouses designed for traditional retail, which struggle to adapt to the fast-paced demands of online shopping(Johan Sunardi, 2023). Batch picking, on the other hand, consolidates multiple orders into a single pick run, potentially reducing travel time and increasing efficiency. However, the complexity of batch creation and the need for subsequent sorting can limit its effectiveness, depending on the warehouse's operational capabilities and technological support (Casella et al., 2023).

Wave picking, a strategy that schedules picking activities in waves to optimize the use of labor and equipment, is less optimal in specific settings due to its rigid scheduling, which may not adapt well to dynamic order profiles or operational disruptions (Li et al., 2022). Despite this, when combined with technologies like Genetic Algorithms, wave picking can significantly reduce picking time, suggesting that its effectiveness is highly contingent on the integration of advanced optimization tools (Ambrosio-Flores et al., 2022). Recent research has also highlighted the potential of collaborative order picking systems (COPS) and robotic mobile fulfillment systems (RMFS), which represent a shift towards more automated and flexible picking strategies. These systems leverage human-robot collaboration and *parts-to-picker* methodologies to enhance picking efficiency, demonstrating significant improvements in order fulfillment speed and accuracy(Damayanti et al., 2022; Dang et al., 2022). The choice of strategy should consider the specific operational context, including order profiles, warehouse layout, and the availability of technological solutions to support efficient order fulfillment processes (Yang Rossomando, 2022).

Optimizing the order-picking process is critical in the supply chain, improving logistics operations' overall responsiveness and agility. Efficient order picking is not only essential to meeting the immediate needs of customers but also has a significant impact on inventory management and logistics costs(Golabek et al., 2021; Pliszczuk et al., 2021; T. Rymarczyk Kłosowski, 2017). By streamlining order fulfillment, companies can reduce the time and resources spent on handling and storing goods, which in turn minimizes costs and improves the flow of goods throughout the supply chain, improving the accuracy and speed of order picking processes, leading to more efficient supply chain logistics (P. Rymarczyk et al., 2021).

The research aimed to optimize order-picking processes in a warehouse through a detailed analysis of a dataset containing information about orders, products, and their locations. The study's novelty lies in its comprehensive approach to understanding the structures and characteristics critical to picking. It involved simulating the picking process with different strategies, including wave picking and grouping methods like single-line and multi-line clustering.

Research Methodology

The research methodology for optimizing the order-picking processes in a warehouse was centered on a detailed dataset analysis, which was prepared for examination. This dataset comprised information about orders, products, and their locations, and its analysis aimed to understand the structures and characteristics vital for the picking process. The data were meticulously prepared and analyzed to comprehend the structure and characteristics of the contained information, establishing a crucial foundation for subsequent research activities. The dataset includes 1050 unique product identifiers and 307046 unique order identifiers. The first five rows of the dataset used for analysis for order picking optimization are shown in Figure 1. The dataset includes the following columns: DATE, which indicates the date the order was placed; OrderNumber, the document number of the order; SKU, the product code or identifier; PCS, the quantity of the product in pieces; ReferenceID, a column used as a key during the merging of the product dataset with the warehouse location dataset; Location, a unique warehouse location key; Alley_Number, the number of the aisle in the warehouse where the product is located; Cellule, the number of the cell in the warehouse where the product is situated; Coord, the x and y coordinates of the product's location in the warehouse; and AlleyCell, a combined identifier of the aisle and cell number where the product is located.

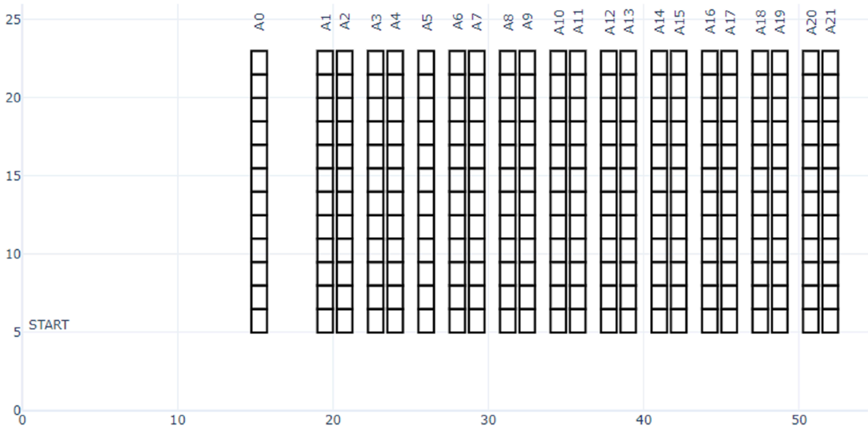
Figure 1. *The first five rows of the dataset*

	DATE	OrderNumber	SKU	PCS	ReferenceID	Location	Alley_Number	Cellule	Coord	AlleyCell
0	2016-04-12	ZS-26770/16/ICK	125215	1.0	399573	A1119504	A11	19	[19.5, 21.0]	A1119
1	2016-11-15	ZS-92872/16/ICK	125215	1.0	399573	A1119504	A11	19	[19.5, 21.0]	A1119
2	2016-11-17	ZS-94113/16/ICK	125215	6.0	399573	A1119504	A11	19	[19.5, 21.0]	A1119
3	2016-11-22	ZS-96213/16/ICK	125215	8.0	399573	A1119504	A11	19	[19.5, 21.0]	A1119
4	2016-11-23	ZS-96968/16/ICK	125215	4.0	399573	A1119504	A11	19	[19.5, 21.0]	A1119

In a warehouse, they move from one location to another while picking shipments, which can account for as much as 60-70% of a picker's time. Reducing transition time is one of the most effective ways to improve warehouse productivity.

The following assumptions were adopted to model the order-picking process: the warehouse was considered in a two-dimensional perspective where racks were low, negating the need for special equipment to access goods. The warehouse housed 22 racks, with products placed in multiple cells. Pickers could only move to subsequent racks via designated cross aisles. Goods were of similar size and weight, and orders were picked in what is known as wave-picking (Liang et al., 2022)Multiple orders were collected during a single route to minimize the distance traveled. The cart used for order picking had a capacity of 20 products, and the picking route started and ended at the exact location. Figure 2 shows a warehouse model with markers on the racks and the start and end points of the route.

Figure 2. *2D warehouse model*



The above assumptions form what is known as the Single-Picker Routing Problem (SPRP)(Scholz et al., 2016). The solution to this problem is to determine the order in which product locations in the warehouse should be visited and the routes that a single picker must take to collect the products that makeup customer orders as quickly as possible.

The problem of determining the route for a single picker represents a specific instance of the general Traveling Salesman Problem (TSP). It was addressed by establishing the sequence in which product locations should be visited, and the routes a single picker must traverse to fulfill customer orders as efficiently as possible. By resolving this problem, the required picking time was considerably reduced, thereby enhancing the operational efficiency of the warehouse. This solution was implemented in Python, allowing for the dynamic calculation of optimal pathways through the complex warehouse layout.

The implementation of the SPRP algorithm was executed in several stages. Initially, the distance between two points within the warehouse was calculated, considering the unique arrangement of aisles. The function designed for this purpose accounted for various movement scenarios between locations, along the same aisle, or across different aisles, utilizing the upper and lower bounds of the aisles.

Subsequently, a function was developed to identify the nearest location from a set of candidates based on the current starting location. This function iteratively sought the closest points, progressively navigating through the warehouse layout.

The next phase involved creating a collection route that minimized the walking distance. The process commenced at the starting point, and then, employing the previously described function, successive locations were determined to be visited until the end of the location list was reached. Upon completing the loop, the order picker returned to the starting point, concluding the route creation process.

Orders within the warehouse were grouped into so-called waves to further optimize the workflow, allowing multiple orders to be fulfilled in a single journey. A mapping function facilitated segmenting the order set into smaller, more manageable groups. For each wave, a list of locations to be visited was determined. Unique coordinates of points were used for this purpose, ensuring that each area was visited only once, even if it contained more than one product.

Simulation of the order picking process in wave picking

For the simulation, a sample of 10,000 orders was extracted from the dataset. The size of the order wave (the number of orders during a single route) varied from 1 to 10. As illustrated in Figure 3, it was observed that the distance required to complete the orders decreased with an increase in the number of orders per wave. With a single order in the wave, the distance needed was approximately 860 kilometers. With two orders in the wave, this value was significantly reduced to about 560 kilometers. Subsequently, the decrease became more gradual, and ultimately, with ten orders in the wave, the distance was reduced to 235 kilometers, which is almost four times less than that required for a single order in the wave.

Figure 3. *Total distance required for order picking, depending on the size of the order wave*

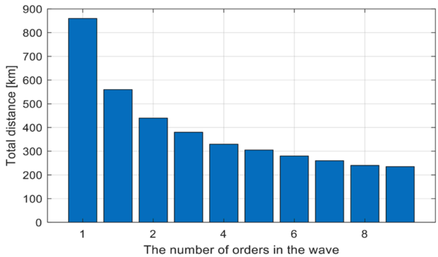
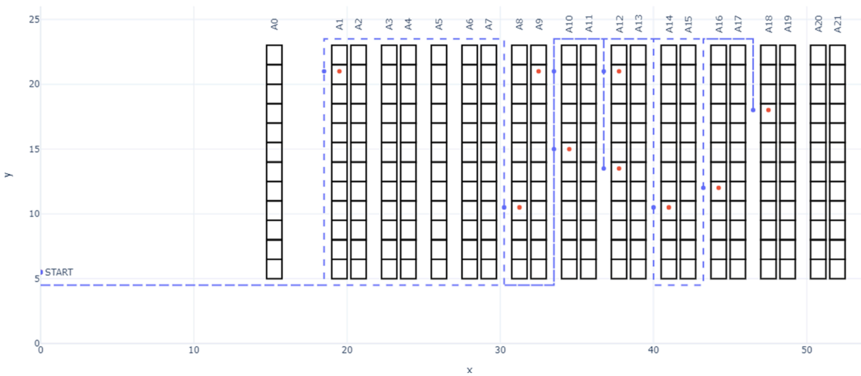


Figure 4 shows the warehouse routing for the first wave of orders, which consisted of 10 orders. Red dots indicate goods in a cell in the warehouse that need to be picked during the picking process. The route is marked with a dotted line, while the blue dots indicate stops.

Figure 4. *Example of routing for one wave of orders (with ten orders per wave)*

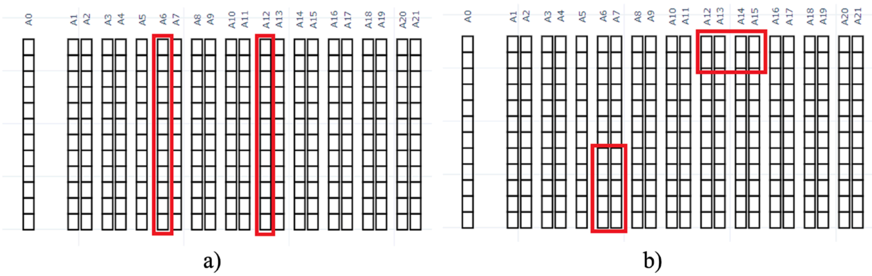


Simulation of the order-picking process with different grouping methods

Another step that can further optimize picking times is clustering. Spatial clustering is the task of grouping a set of points so that objects in the same cluster are more similar than objects in other clusters. For a two-dimensional warehouse model, two types of clustering can be proposed:

- single-line clustering – a grouping of products located within a single aisle (Figure 5a);
- multi-line – a grouping of products located in multiple aisles (Figure 5b).

Figure 5. *The idea of grouping: a) single-line, b) multi-line*



In warehouse operations, the similarity metric was defined as the necessary walking distance between one location and another. For example, locations were grouped so that the maximum walking distance between any two locations did not exceed 10 meters. Due to the specific layout of the aisles in the warehouse, conventional distance metrics such as the Euclidean distance could not be applied, as they would significantly differ from the distance that needed to be covered between two points. A diagram of how to perform order-picking simulations with order grouping is shown in Figure 6.

Figure 6. *A diagram of how to perform order-picking simulations with order grouping*

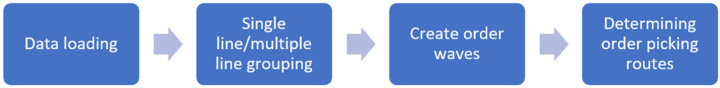


Figure 7. *Simulation results for 100 orders for single-line and multi-line groupings*

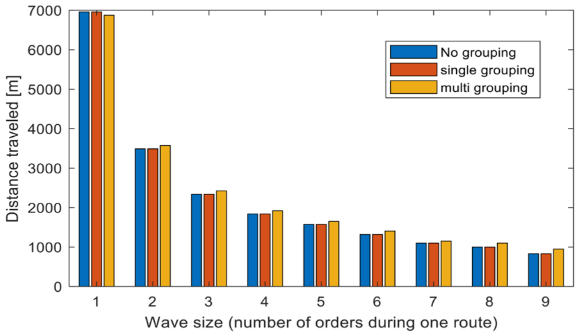


Figure 7 shows simulation results for 100 orders for single and multi-line groupings. For the collection studied, grouping has no positive effect on picking. Single-line clustering only improves the non-grouping method in the first case. In contrast, multi-line grouping usually causes a slight deterioration in the distance traveled in the warehouse. However, it should be remembered that clustering can positively affect other data sets, so these methods should be checked when analyzing a new data set.

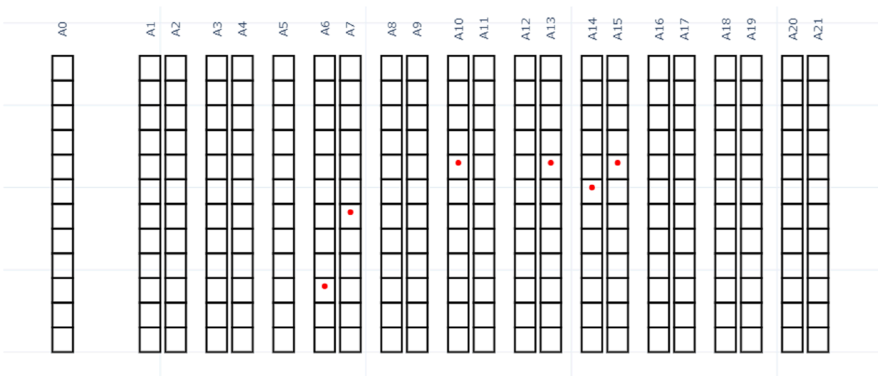
Routing for orders from a selected day

The following is an example of determining the route for a single day's orders from the database when there were six orders (Figure 8). Each order contained one or more units of a given product, with a maximum of 14 units in the case of the second order. The location of products in the warehouse (marked with red dots) that are in order is shown in Figure 9.

Figure 8. *Orders from selected as an example of routing during the picker's workday*

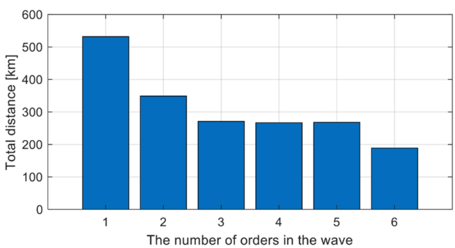
	DATE	OrderNumber	SKU	PCS	ReferenceID	Location	Alley_Number	Cellule	Coord	AlleyCell	AlleyNumber
0	2018-10-03	ZS-94516/18/ICK	124502	4	362502	A1505401	A07	5	[42.25, 16.5]	A1505	A15
1	2018-10-03	ZS-94437/18/ICK	121906	14	135079	A1005305	A12	5	[34.5, 16.5]	A1005	A10
2	2018-10-03	ZS-3468/18/FE	115593	1	263738	A1406201	A08	6	[41.0, 15.0]	A1406	A14
3	2018-10-03	ZS-94632/18/ICK	118813	2	391450	A1305102	A09	5	[39.0, 16.5]	A1305	A13
4	2018-10-03	ZS-94555/18/ICK	115267	1	319773	A0610204	A16	10	[28.0, 9.0]	A0610	A06
5	2018-10-03	ZS-94622/18/ICK	118879	1	267290	A0707301	A15	7	[29.25, 13.5]	A0707	A07

Figure 9. *The location of products in the warehouse (products marked with red dots)*



Below are the results of simulations for selected orders, where a significant reduction in the distance needed to traverse the warehouse was observed. In the case study of orders from a given day, the total distance required to complete the order was successfully reduced from 532 meters to 189 meters by processing several orders in one wave.

Figure 10. *The result (total distance) from the simulation for the orders of the set day*

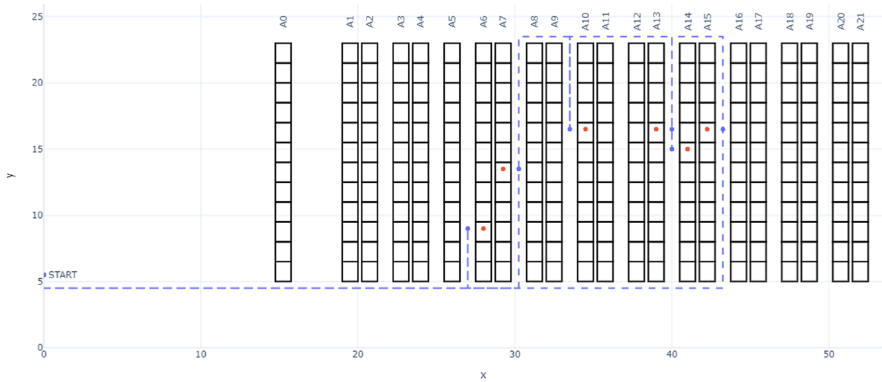


When each wave is composed of a single order, it is evident that each order is processed individually. In scenarios where two orders are executed per wave, the examined range of orders will be fulfilled throughout three waves. In the first wave, products A0707 and A1406 were retrieved. The second wave encompassed the retrieval of products A0610 and A1505, while the third wave involved the collection of products A1005 and A1305. When operating with three orders per wave, there will be two complete waves of orders. For the execution of four or five orders within a wave, the first wave will consist of four or five products, and the second wave will contain two or one product, respectively. Undertaking at least six orders per wave implies that all orders will be processed simultaneously, given that precisely six orders were placed on the day under consideration. An example of the result of the wave order splitting algorithm is shown in Figure 11 Figure 12 shows the optimal route, determined by executing 6 orders during the wave.

Figure 11. *An example of the result of the wave order splitting algorithm*

	wave	distance	routes	order_per_wave
0	0	100	[[0, 5.5], [41.0, 15.0], [0, 5.5]]	1
1	1	74	[[0, 5.5], [29.25, 13.5], [0, 5.5]]	1
2	2	62	[[0, 5.5], [28.0, 9.0], [0, 5.5]]	1
3	3	106	[[0, 5.5], [42.25, 16.5], [0, 5.5]]	1
4	4	90	[[0, 5.5], [34.5, 16.5], [0, 5.5]]	1
5	5	100	[[0, 5.5], [39.0, 16.5], [0, 5.5]]	1
6	0	116	[[0, 5.5], [29.25, 13.5], [41.0, 15.0], [0, 5.5]]	2
7	1	112	[[0, 5.5], [28.0, 9.0], [42.25, 16.5], [0, 5.5]]	2
8	2	121	[[0, 5.5], [34.5, 16.5], [39.0, 16.5], [0, 5.5]]	2
9	0	122	[[0, 5.5], [28.0, 9.0], [29.25, 13.5], [41.0, ...	3
10	1	149	[[0, 5.5], [34.5, 16.5], [39.0, 16.5], [42.25,...	3
11	0	146	[[0, 5.5], [28.0, 9.0], [29.25, 13.5], [41.0, ...	4
12	1	121	[[0, 5.5], [34.5, 16.5], [39.0, 16.5], [0, 5.5]]	4
13	0	168	[[0, 5.5], [28.0, 9.0], [29.25, 13.5], [34.5, ...	5
14	1	100	[[0, 5.5], [39.0, 16.5], [0, 5.5]]	5
15	0	189	[[0, 5.5], [28.0, 9.0], [29.25, 13.5], [34.5, ...	6

Figure 12. *The optimal route, determined with the execution of 6 orders during the wave*



Conclusions

The research aimed to enhance the warehouse's productivity by optimizing the routing of individual order fulfillment and conducting an analysis that determined the shortest route in the order-picking process, taking into account the tools utilized, the warehouse layout, and a map of the products contained within.

The method applied significantly reduced the distance that the order picker needed to traverse in the warehouse. One of the critical elements of optimization was the consolidation of orders into waves of a selected size. This stage allowed for approximately a fourfold reduction in the distance for the dataset under study.

The proposed solution also included grouping products based on their location in the warehouse (grouping along a single aisle or multi-aisle grouping based on the proximity of the distance to be traveled between cells). While this approach often yields improved results(*Improve Warehouse Productivity Using Spatial Clustering with Python | Towards Data Science*, n.d.), it did not do so in the case of the dataset studied. The solution with grouping was presented because it might perform better on another dataset and allow for further reduction of the distance necessary to be traveled in the warehouse.

The volume of the goods being compiled could also be considered in potential further development of the method. At this point, the algorithm assumes that the picking cart can accommodate ten orders. As seen in the example, these are goods of relatively similar volume, such as tables, chairs, and poufs. However, a problem could arise with goods whose volume significantly exceeds the standard. Conversely, with more miniature goods, it would be possible to collect more at once, instead of limiting to 10 pieces. In summary, it can be stated that the assumption adopted would work well only in cases where all goods in the warehouse are similar in volume.

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