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The Optimization of Picking in Logistics Warehouses in the Event of Sudden Picking Order Changes and Picking Route Blockages

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Abstract: (1) Background: This work focuses on improving the efficiency of warehouse operations with the goal of promoting efficiency in the logistics industry and mitigating logistics-related labor shortages. Many factors are involved in warehouse operations, such as the optimal allocation of manpower, the optimal layout design, and the use of automatic guided vehicles, which together affect operational efficiency. (2) Methods: In this work, we developed an optimal method for operating a limited number of workers or picking robots in a specific area, coping with cases of sudden disruptions such as a change in picking order or the blockage of aisles. For this purpose, the number of pickers, the storage capacity, and other constraints such as sudden changes in picking orders during the picking process, as well as blockages in the aisles of a warehouse site, are considered. The total travel distance is minimized using Gurobi, an optimization solver. (3) Results: The picking routes were optimized in three different scenarios using the shortest route between the starting point and the picking points, resulting in up to a 31% efficiency improvement in terms of the total distance traveled. (4) Conclusions: The main contribution of this work is that it focuses on the day-to-day work situations of sudden changes in the picking order and the presence of route blocks in real-world logistics warehouse sites. It demonstrates the feasibility of responding to sudden disruptions and simultaneously optimizing picking routes in real time. This work contributes to the overall efficiency of logistics by providing a simple, yet practical, data-driven solution for the optimization of warehouse operations.

Keywords: mathematical optimization; Gurobi; order picking; warehouse operations; logistics; warehouse layout

MSC: 90B06

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1. Introduction

In recent years, there has been a remarkable increase in the global movement of goods and a corresponding increase in the demand for warehousing. Warehousing is essential to supply chain management (SCM) because it is responsible for storing not only finished products, but also parts and materials [1]. It also collects materials from suppliers around the world and makes them available in a streamlined and consistent manner. Efficient warehouse operations are critical to maintaining logistics' efficiency. Warehouse efficiency contributes to overall logistics efficiency, making warehousing an important sector that connects every country with the world.

In this work, we focus on the optimization of picking routes in a warehouse with a simple layout. There are two motivations behind this approach. First, the limited availability of space. The land available for warehouses in a country like Japan is very limited. Warehouses and cargo handling facilities are densely clustered around terminals along the coast, and there is no room to build large warehouses.

Second, warehouse operations are subject to sudden disruptions such as picking order changes and aisle blockages. A picking order change occurs when there is an update of the items to be shipped/picked or a change in staffing. Aisle blocking occurs when a forklift is parked in the aisle; carts or pallets with products on them are sitting in the area; or someone else is picking in the area. These disruptions often lead to changes in picking routes. It adds value to optimize picking routes while managing these disruptions in real time to generate cost and time savings.

The elements of a warehouse's layout include everything from the volume of the warehouse itself to the number of employees, the design and arrangement of racks, and so on. By adjusting these factors, it is possible to improve the efficiency of warehouse operations. In addition, the replenishment of inventory may not be smooth, resulting in significant losses of time and manpower. Optimizing picking routes is an important part of warehouse operations. A simple but realistic study is needed. Therefore, the purpose of this work is to optimize picking activities in warehouses.

The aim of this work is to optimize picking routes, taking into account various on-site factors such as sudden changes in picking orders and unexpected aisle blockages. We proposed a simple model with low computational resources and a fast execution to optimize the picking route. The results show that the proposed model can optimize picking routes by 20% to 31% without negatively affecting service responsiveness.

The main contributions of this work are threefold. First, it takes into account the actual working situation in a logistics warehouse. Second, it proposes a method for improving order picking efficiency by 20–31% without compromising service responsiveness, thus leading to cost savings for logistics companies. Third, it provides a scalable solution that can be applied to warehouses of different sizes.

In summary, this research demonstrates the feasibility of responding to and optimizing changes in the picking workload in real time. This makes it possible to improve work efficiency while maintaining the desired level of service responsiveness. In essence, this work has developed a method to optimize picking routes, taking into account real-world operational constraints, and has been able to achieve significant efficiency gains without compromising customer service. This highlights the potential for improving warehouse productivity through advanced planning and optimization techniques.

Various studies (such as [2,3]) have discussed green scheduling while mainly focusing on manufacturing sites. This research focuses on green scheduling in the warehousing sector, thus complementing the existing literature.

The rest of the paper is organized in the following manner: Section 2 reviews previous studies. Section 3 explains the model used and proposes a solution. Experiments and results are presented in Section 4, and the effectiveness of the proposed method is demonstrated based on the experimental results. Section 5 discusses the findings. Finally, Section 6 contains a discussion of improvements and developments.

2. Previous Studies

Order picking refers to the picking operations in units of placed orders. Order picking is a critical and costly activity in warehouses, accounting for up to 55% of all warehouse operating costs [4]. Layout design and routing are two of the most important research areas here [5]. Layout design-related research investigates ways to reduce picking time through efficient product placement and flow design [6]. Routing-related research investigates ways to reduce picking time by optimizing the picker's route [3,4,6].

2.1. Layout Design

A number of studies, such as [7–10] have been carried out on warehouse layouts. For example, Cardona et al. [9] conducted a study using a fishbone layout with diagonal cross aisles instead of the traditional layout with long and wide aisles that is the main one used worldwide. Zhou et al. [11] researched picking strategies for a leaf layout warehouse. Liu et al. [12] studied the best picking path for a chevron layout warehouse.

One of the research areas related to warehouse layouts is the application of the Internet of Things (IoT). Trab et al. [10] presented their research on layout and picking routes using Radio Frequency Identification (RFID) based on product compatibility. Lee et al. [13] proposed a warehouse management system for intelligent logistics using the IoT. The authors proposed a picking method suitable for a warehouse management system using data including factors such as the number of employees and SKUs (stock keeping units), with the aim of improving the efficiency of warehouse management. Their proposal is based on fuzzy theory, prioritization, and a comparison of picking methods. Their research results show that their proposed method improves warehouse management efficiency and warehouse productivity by reducing picking time. The method used in their paper to determine the best picking method was considered to be very useful; however, certain aspects need to be improved in terms of its complexity and flexibility.

2.2. Route Optimization

There are several ways to improve the efficiency of picking operations, such as optimizing locations [8], standardizing work rules [14], and optimizing picking routes [12].

2.2.1. Optimization of the Distance between Two Points

A picking route is optimized by minimizing the distance between two points. Shetty et al. [1] used the Gurobi solver and the Julia programming language to optimize a picking route. The authors compared two sample picking routes: one with locations uniformly distributed throughout the warehouse and another with differentiated locations. A simple distance matrix approach was used to perform the optimization (Figure 1).

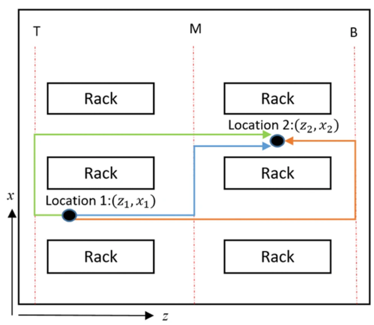


Figure 1. Image of optimization of two points (Shetty et al. [1]).

In particular, a simple layout was used with three vertical racks and two horizontal racks, with an aisle between each of the racks. In this case, there were three possible picking routes. Figure 1 shows the proposed route from Location 1 to Location 2: the first route is from Location 1 to the left, moving outside the racks; the second route is from Location 1 to the right, moving outside the racks; and the third route uses the aisles between the racks. In this case, the minimum of the three proposed routes is used to determine the optimal route between the two points. This approach is flexible, simple, and effective because it can accommodate changes in the number of racks and corridors.

2.2.2. Optimization of the Routes of Order Picking with Two or More Aisles

Roodbergen and Koster [15] suggested that adding cross aisles to the warehouse layout can reduce order fulfillment time. The authors studied five picking routes to determine the optimal routes (Figure 2). The first is the most basic S-shape method. This method requires the worker to pass through each passageway at least once, resulting in the greatest total distance traveled. The second is called the return method. In this method, the worker returns to the lower aisle after picking each item in each aisle. The third method, the mid-point method, picks from the upper or lower aisle that is closer to the picker. This method is very effective when the number of items picked per aisle is small. The fourth method, with the largest gap heuristic, considers the case where there are multiple orders in an aisle and picking from one side is preferable to picking from both the upper and lower aisles. This method always gives better results than the mid-point method. The fifth method, the combined method, combines the above four methods to suggest a route, from which the optimal route was suggested.

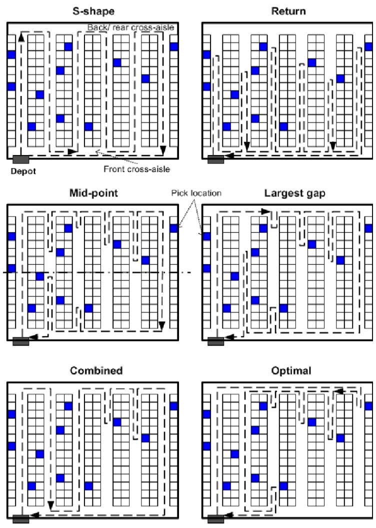


Figure 2. Image of order picking route optimization. The dotted lines represent the picking routes. (Roodbergen and Koster [15]).

In this work, picking route optimization is performed under the assumption that locations are constant and work rules are uniform.

2.2.3. Methodologies for Picking Route Optimization

Order picking route optimization is a process of identifying the order picking sequences in a picking route to minimize the travel time/distance. Picking route optimization techniques can be categorized into three types: exact, heuristic, and meta-heuristic algorithms [16]. Exact algorithms are usually based on enumeration or cutting plane methods. The advantage is that they systematically explore the realizable region of the problem and eliminate suboptimal solutions. However, they have some limitations, such as being computationally expensive, requiring large amounts of memory or storage. Heuristic algorithms are methods that use intuition, general rules, or experience to find a solution to an optimization problem. Heuristic algorithms are often faster and simpler than exact algorithms and can handle large or complex problems. However, the solution found is not guaranteed to be the best. Few studies have proposed exact algorithms [17]. In this paper, we propose an exact algorithm that requires minimal computational resources.

2.3. Our Research Motivation

In the existing literature, the optimal picking route has been derived by the search for the shortest distance between two points. However, these studies did not address the model's lack of simplicity, the complexity of its implementation, and the sudden change in picking tasks in the field. To overcome these challenges, in this research we propose a model which has simplicity and practicality by considering the actual reality of warehouses based on warehouse workers' feedback, such as sudden changes in picking tasks (change of the picking order during the picking process, or order changes, and henceforth) and blockages existing in the aisles in a warehouse.

3. Model

Figure 3 presents the flowchart of the three scenarios used in this work.

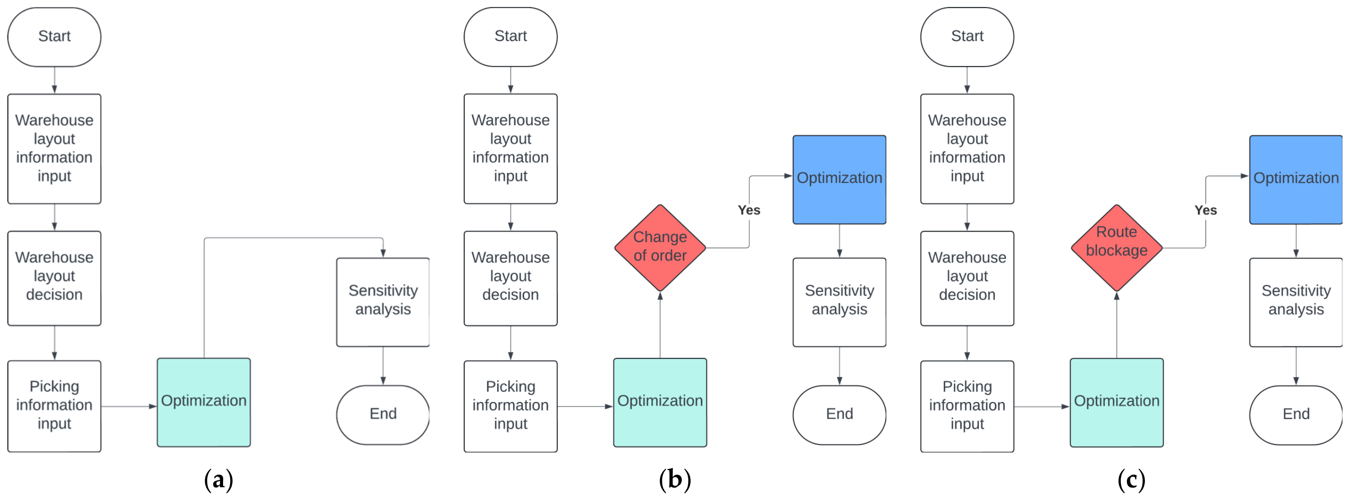


Figure 3. (**a**) Basic scenario; (**b**) picking order change scenario; (**c**) route blockage scenario.

In the first scenario, we constructed a flow to analyze the efficiency of the optimization of general picking (Figure 3a). First, information about the warehouse layout, such as the number of aisles and racks, was specified and, based on the layout information and the picking location, the order was randomly determined. Then, the picking routes were compared, and a sensitivity analysis was performed to verify the efficiency improvement of the optimized picking routes.

In the second scenario, we constructed a flow (Figure 3b) to analyze the efficiency of picking optimization in a sudden order change situation. Order changes occur when there is an update to the items to be shipped/picked, or when there is a change in personnel assignments. This flow covers cases where an order change occurs in the middle of an optimized route.

In the third scenario (Figure 3c), we constructed a flow to analyze the efficiency of optimization when picking in the case of a blockage. This scenario covers cases where a blockage appears in the route. Aisle blocking occurs when a forklift is parked in the aisle; carts or pallets with products are stopped in the aisle; or someone else is picking in the area.

3.1. Layout Model

To begin with, a simple conventional warehouse layout is used in this work (Table 1). First, basic information such as the warehouse's size and capacity are specified, and the warehouse layout is determined based on this information.

Table 1. Warehouse layout information.

Layout Information	Abbreviation and Sample Values
Number of vertical aisles	St_aisle (e.g., 10)
Number of horizontal aisles	Cross_aisle (e.g., 3)
Number of vertical product storage spaces per rack	Vertical_rack (e.g., 4)
Number of horizontal product storage spaces per rack	Horizon_rack (e.g., 2)
Number of vertical racks	Num_vertical (e.g., 2)
Number of horizontal racks	Num_horizon (e.g., 9)
With or without outer rack	Yes or No (e.g., No)

From the information presented above, it is possible to draw the warehouse layout to determine the picking locations of the products. In this paper, two types of warehouse layouts are used: one is the size of the actual site and the other is a larger scale warehouse used in the analysis.

Other details that affect the layout include ABC priority, the number of rack levels, and the location of the picking point. ABC priority is a method for determining where to store products based on how frequently they are picked. Increasing the number of tiers increases the number of SKUs that can be stored. If the racks are too large, they may be out of the picking range of a human or a robot. It is necessary to select racks within the picking range, taking into account the size of the products to be stored and the size of the warehouse itself. In addition, the shortest route can be changed by changing the location of the picking point, which is the starting point of the picking.

In this work, simulations are conducted using a conventionally simple layout to avoid complexity and without using data on product size, human or robot picking range, or other factors.

3.2. Picking Model

3.2.1. Baseline Scenario

The initial step is to enter the baseline information (Table 2). The orders are added using a list of orders (a), with the order locations as ordered values. The start and end points of the picking route, the depots (start points), are included at the beginning of the order list. The picking points are randomly selected from all the picking points in the warehouse layout. In our simulation, the number of pickers is set to 1.

Table 2. Baseline scenario's picking information.

Layout Information	Abbreviation and Sample Values
List of orders	a
Number of pickers	1 or p (e.g., 1)

We propose a mathematical formulation of the model. The set of all nodes a consists of all work locations, with each work location as a node, and $node(x, y) = (0, 0)$ indicates the depot (starting point). The number of nodes is $N = length(a)$. The average speed of the movement between nodes i and j is constant. The 0, 1 variable $x_{i,j}$ is used as an indicator of the movement from node i to node j, where 1 means movement between each node and 0 means otherwise.

$$min \sum_{i \in N} \sum_{j \in N} x_{ij} l_{ij} \tag{1}$$

$$\text{subj to} \sum_{i \in N} x_{ij} = 1 \quad \forall j \in N \tag{2}$$

$$\sum_{j \in N} x_{ij} = 1 \ \ \forall i \in N \tag{3}$$

$$x_{i,j} = \{0, 1\} \tag{4}$$

$$u_i - u_j + N x_{ij} x \le N - 1 \quad \forall i, j \in N \tag{5}$$

The goal of this optimization model is to find the shortest path, the optimal solution, if the picker starts from the starting point, passes through all specified nodes, and returns to the starting point.

The objective function (1) of the mathematical optimization model shows the minimization and optimization of the total travel distance of the order picking route. Constraints (2) and (3) indicate that one edge enters and one edge leaves each node, i.e., there is only one visit per node. Constraint (4) states that $x_{i,j}$ is a 0, 1 variable. Constraint (5) is a constraint used to eliminate subroutes. The variable u_i is the value for each node except the depot. It is applied following the Miller–Tucker–Zemlin (MTZ) formulation to remove subroutes.

3.2.2. Scenario of Order Change

In real workstations, orders are often suddenly added or deleted during the picking process. The current position is called "now" and is a number on the list. If the "now" position is a large number, the picking route itself becomes short, so we randomly selected from three points in the first half of the picking route. When deleting, the coordinates to be deleted are set to "delete" status and the corresponding number is deleted from the Pick

Order list. Deletion is also chosen randomly, so that now < delete < length(a) − 1. To add a job, we use add as the coordinates of the job to be added. Add is appended to the end of the list. Using each of these expressions (Table 3), we perform a new route optimization. A flowchart is added to show the process.

Table 3. Picking order change information.

Layout Information	Position Expression
Current situation	now $\{now \in 1, 2, 3\}$
Situation of job deletion	delete∈[now, length(a) − 1]
Situation of job addition	add = [(x,y)]

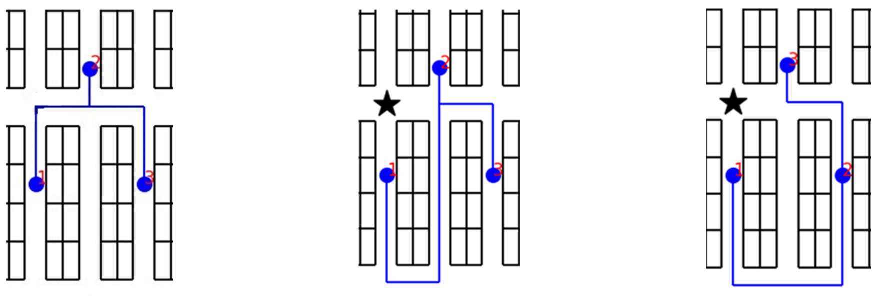
Moreover, in this case, unlike the baseline optimization, the end point and the start point are different. Therefore, if i = 0 is the start point (current position) and i = 10 is the end point, the following objective function and constraints are added:

$$min \sum_{i \in N} \sum_{j \in N} x_{ij} l_{ij} - l_{10,0} \quad (6)$$

$$\text{Subj to } x_{10,0} = 1 \quad (7)$$

3.2.3. Scenario of Route Blockage

Sudden route blocks at actual locations are an obstacle to efficient order picking. Since this work considers the impact of route blockages on the optimal route, the points to be blocked are limited to those on the optimized route. Therefore, a node between two points i and j is randomly selected from all picking routes, and the simulation is performed by blocking the closest intersection of edge i that is on the adopted route. For a change in the picking route due to route blocking, consider the case shown in Figure 4 below. In this case, if a blocking point appears on the optimized route as shown in Figure 4a, the total distance traveled becomes large if the points are visited in the same order to avoid the blocking point, as shown in Figure 4b. Therefore, by performing the optimization as shown in Figure 4c, it is possible to optimize the picking route while avoiding the blocked points in the optimal order.



(**a**) (**b**) (**c**)

Figure 4. Change in picking route due to route blocks. (**a**) Optimization before route blockage; (**b**) before optimization with route blockage; (**c**) optimization with route blockage. The numbers indicate the order in which picking is performed. The star indicates a route blockage.

From the figure above, we can see that roadblocks cause changes in routes and the shortest paths. The model is simulated using the following information (Table 4).

Table 4. Route blockage picking information.

Layout Information	Abbreviation and Sample Values
Randomly chosen node (*i*,*j*)	$(s, s+1)$ $\{s \in N-1\}$
Point to be blocked	block = (x,y)

3.3. Analysis Model

To evaluate the accuracy of the model to be optimized, a sensitivity analysis is performed. The reason for performing a sensitivity analysis is to evaluate, quantitatively and qualitatively, how much a change in the optimization affects the results. The following formula is used to evaluate the accuracy of the model:

$$S(x) = \delta y(total\ travel\ distance)/\delta x(change) \tag{8}$$

The x parameter specifies the amount of change. For baseline picking optimization, the parameter x is the number of all orders; for order change optimization, the parameter x is the number of orders that have changed; and for picking optimization with blocking points, the parameter x is the number of points to be blocked.

The computation is carried out using Gurobi Optimizer version 10.0.1 in the Python 3.10.11 environment. The Gurobi Optimizer is a high-performance solver that incorporates the latest technologies into mathematical optimization. The Gurobi Optimizer has a growing community of users because it derives optimal solutions quickly and accurately. The simulations are performed on a Fujitsu LIFEBOOK MH75 laptop with Core i5 CPU and 8 GB RAM running the Windows 11 operating system.

4. Experiments

In this section, storage facilities close to the actual size of warehouses were used and routes were compared to the optimal solution (sample numbers in Table 1). The layout is plotted in Figure 5. From the plot, the candidate picking locations are x = [0, 1, 2, 3, 4, 5, 6, 7, 8, 9] and y = [1, 2, 3, 4, 6, 7, 8, 9]. The computation is carried out with the Gurobi solver using the Python language.

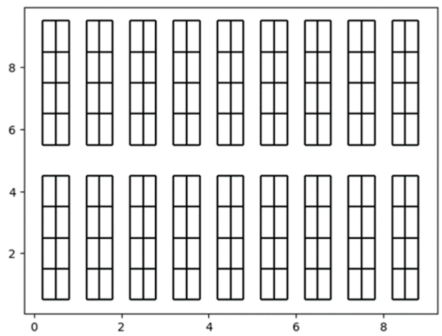
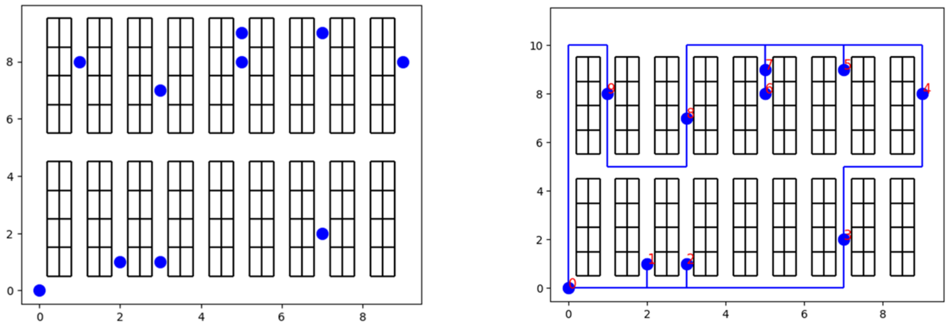


Figure 5. Plotted layout.

4.1. Baseline Scenario

First, we plot the jobs for the base situation. The elements of the job location used in the simulation are randomly selected from the depot (0,0) and nine candidate picking locations corresponding to the layout of the racks. The list a = [(0,0), (7,9), (2,1), (5,9), (5,8), (3,1), (9,8), (1,8), (7,2), (3,7)] of work locations proposed here is also used in the simulation. List a is plotted against the warehouse layout in Figure 6a.



(**a**) (**b**)

Figure 6. (**a**) Plot of order on warehouse layout; (**b**) optimized route. The numbers indicate the order in which picking is performed.

Next, the shortest route between the two points was computed for optimization. The results are shown in Figure 6b.

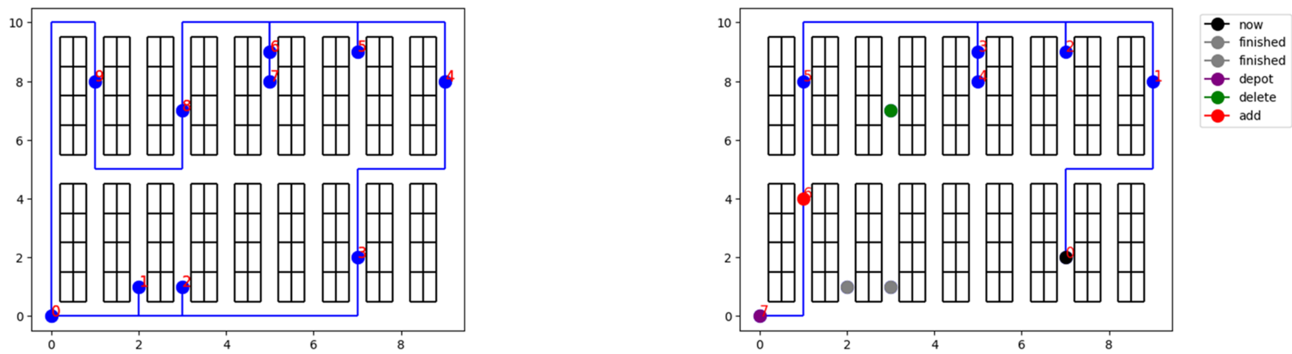
The optimization results are summarized in Table 5.

Table 5. Optimization solutions for baseline scenario.

Layout Information	Abbreviation and Sample Values
Total distance traveled	86
Movement between two points (*i*,*j*)	[(0,5), (5,8), (8,6), (6,1), (1,4), (4,3), (3,7), (7,9), (9,2), (2,0)]
Route order of coordinates (*x*,*y*)	[(0,0), (3,1), (7,2), (9,8), (7,9), (5,8), (5,9), (1,8), (3,7), (2,1), (0,0)]

4.2. Scenario of Order Change

In this section, simulations were performed using randomly selected order change information, such as *a* = [(0,0), (3,1), (7,2), (9,8), (7,9), (5,8), (5,9), (1,8), (3,7), (2,1)], with the now position as 3, the delete position as 7, and add position as [(6,4)]. The original optimized route and the optimized route after the order change are shown in Figure 7.

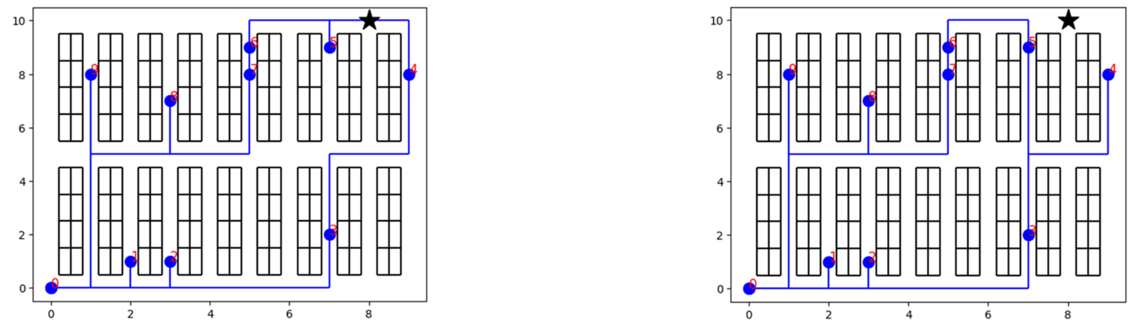


(**a**) (**b**)

Figure 7. (**a**) Original optimized route; (**b**) optimized route after order change. The numbers indicate the order in which picking is performed.

4.3. Scenario of Route Blockage

In this section, simulations were performed using the randomly selected blocked positions as a set order list *a* = [(0,0), (7,9), (2,1), (5,9), (5,8), (3,1), (9,8), (1,8), (7,2), (3,7)]. The optimized route before blockage and after blockage is shown in Figure 8.



(**a**) (**b**)

Figure 8. (**a**) Optimized picking route before blockage; (**b**) optimized route after blockage. The numbers indicate the order in which picking is performed. The star indicates a route blockage.

4.4. Scenario of Expansion

In this section, a comparison is made with a scaled version of the warehouse. For optimization comparisons, randomly selected picking orders were repeated 10 times and averaged for comparison. The results are plotted in Figure 9.

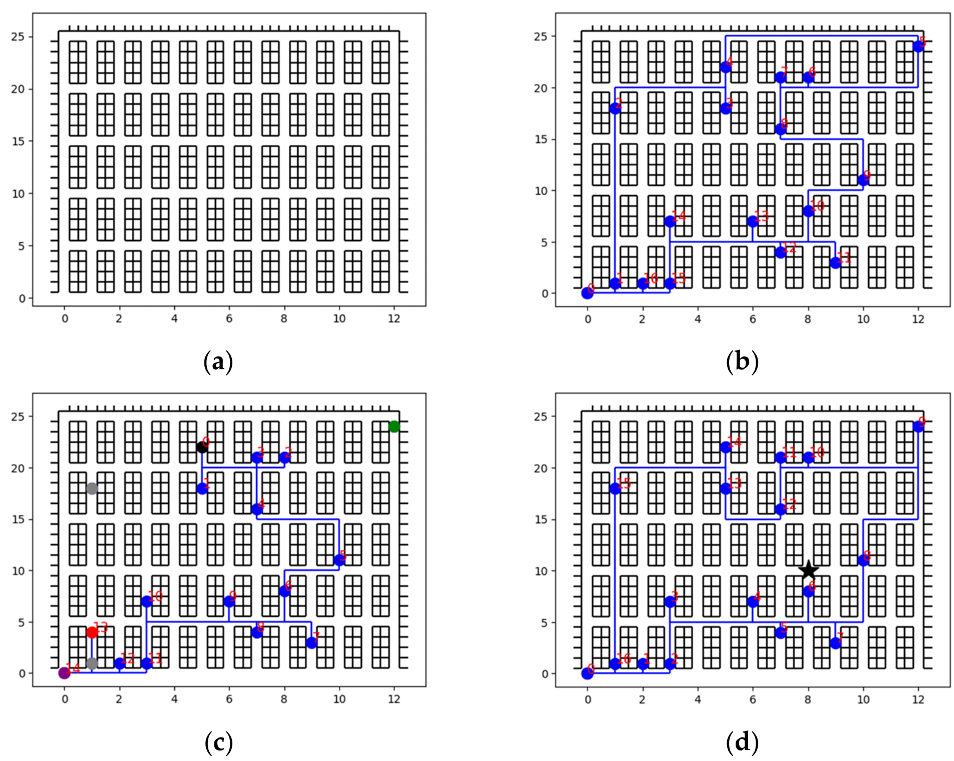


Figure 9. (**a**) Plot of scaled layout; (**b**) optimized route of baseline scenario; (**c**) optimized picking route after order change; (**d**) optimized route after blockage. The numbers indicate the order in which picking is performed. The star indicates a route blockage.

4.5. Summary of Results

Ten simulations of each of the three scenarios shown in Figure 9b–d were conducted. The simulation results are summarized in Table 6. All experiments were executed in less than 10 s, even on a standard laptop, which is extremely fast. Therefore, reports of the running time are omitted.

Table 6. Summary of simulation results.

Scenario	Number of Simulations	Distance before Optimization	Distance after Optimization	Reduction in Distance	Sensitivity Index
Baseline scenario	1	200	187	7%	13
	2	190	128	48%	62
	3	182	140	30%	42
	4	182	142	28%	40
	5	182	144	26%	38
	6	172	158	9%	14
	7	198	164	21%	34
	8	154	132	17%	22
	9	146	140	4%	6
	10	180	152	18%	28
	Average	178.6	148.7	20%	29.9
Order change scenario	1	182	130	40%	52
	2	148	114	30%	34
	3	131	95	38%	36
	4	130	116	12%	14
	5	115	101	14%	14
	6	161	115	40%	46
	7	188	128	47%	60
	8	126	90	40%	36
	9	124	112	11%	12
	10	139	105	32%	34
	Average	144.4	110.6	31%	33.8
Route blockage scenario	1	162	162	0%	0
	2	134	134	0%	0 *
	3	144	144	0%	0 *
	4	142	142	0%	0 *
	5	146	146	0%	0 *
	6	164	162	1%	2 *
	7	164	164	0%	0
	8	140	134	4%	6 *
	9	144	140	3%	4 *
	10	156	156	0%	0
	Average	149.6	148.4	1%	4

* Indicates that the picking sequences of the route are updated.

5. Discussion

In the baseline scenario, the shortest path between two points was derived and efficiency improvement methods were considered in terms of the distance traveled. From the analysis we know that 10 simulations of an order consisting of 16 nodes were performed, with a maximum sensitivity index of 62, a minimum of 6, and an average of 29.9. Optimization reduced the total distance traveled by 20%. The maximum and minimum results also confirm that the bias in total distance is caused by the bias in the picking order’s location, and it is clear that optimization has a significant impact on the picking route depending on the nature of the order. This bias may be due, in part, to not having considered zoned picking and product classifications.

In the picking order change scenario, optimization is performed taking into account site factors and changes such as picking order additions and deletions. The simulation results indicate that a large reduction in the total distance traveled was observed. The results show that the maximum sensitivity index was 60, the minimum was 12, and the average was 33.8 when adding a picking order and deleting a picking order, over 10 simulations. Optimization reduced the total distance traveled by 31%. The improvement is significant, but there is a limitation in that the reduced values are sensitive to the end point and the added point.

In the route blockage scenario, in general, the optimization corresponding to the route blockage did not result in significant changes in the distance traveled. In this case, a route blockage at one node was considered and a comparison was made over 10 simulations, resulting in a maximum sensitivity index of 6, a minimum of 2, and an average of 4. Optimization resulted in an average decrease of 4 per change. In terms of the total distance traveled, the optimization resulted in a decrease of only 1%. However, it should be noted that the picking sequences of the picking routes were updated in 7 out of 10 simulations, indicating that the optimization was successful. There are two possible reasons for the change in the picking route. First, there may be an alternative route close to the specified route. Second, the change in the optimized total travel distance may change significantly when the blocks are close to an area where picking orders are concentrated.

Based on the results of the sensitivity analysis, and compared to the baseline scenario, changing the picking order has a higher impact while blockages in the picking route have a lower impact on the route optimization results. This indicates the importance of route optimization when the picking order is changed during the picking process.

As a result, the optimization of the picking route using Gurobi was able to improve efficiency. In particular, Gurobi was able to smoothly guide the optimized route when dealing with sudden order changes. By having pickers carry smart tablets to receive information during the picking process, route optimization can be performed and the warehouse company can respond to changes as quickly as possible. In the route blockage scenario, the number of changes that occurred was fewer than we expected. It is necessary to revise the conditions of the nodes' selection in future studies, so that the proposed model can be used for different on-site situations.

6. Conclusions and Limitations

In this work, order picking optimization was performed considering different real on-site conditions of order picking in a warehouse. A simple but practical approach was used to perform the optimization, resulting in reduced travel distances and increased route efficiency. Most importantly, it provides flexibility for the warehouse to respond in real time to sudden disruptions such as changes in picking tasks and route blockages in a warehouse.

The constraints were kept as simple as possible to be practical. Comparisons were made through a sensitivity analysis to intuitively identify areas for improvement, resulting in a reduction in the total travel distance and improved picking efficiency. The optimization was based on actual situations that occur in real warehouse operations, such as changes in picking orders and the presence of blockages in warehouse sites. In addition, the actual size of the warehouse and the type of work were considered in the experiments. The results show that our proposed algorithm could reduce the total travel distance by 20% in the baseline scenario and by 31% in the picking order change scenario. In total, 70% of the routes were updated to alternative routes in the blockage scenario.

Our research contributes to warehouse operations in three ways:

(1) It takes into account the actual size and working situations in a warehouse. The model itself is easy to implement, and each of the optimizations takes less than 10 seconds, which can be performed by the picker in the field using a smart tablet to obtain real-time picking route guidance. As such, it is highly practical.

(2) It improves order picking efficiency by 20–31% without compromising service responsiveness, which directly leads to cost savings for logistics companies.

(3) The model can be enriched/extended to deal with other actual on-site scenarios, and it can be easily scaled to optimize order picking for warehouses of different sizes.

In future studies, two points of improvement could be considered. First, the complexity of the model. In this work, a simple model was constructed with a focus on easy implementation. The model could be further extended to include more constraints, such as intersections on the route and capacity constraints, so that it can handle optimization for automatic robot picking. Second, the implementation of dynamic simulations. In this work, picking with only one picker was considered, but in a real warehouse, many workers work in the same place at the same time, and there are problems that cannot be understood simply by plotting an optimized picking route. From this point of view, simulating their movement along their picking route over time would contribute further to on-site picking optimization. In addition, introducing RFID information would make it possible to include location data in these simulations. This would make it possible to determine the exact shortest route.

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