Generating Products Placement in Warehouse Using BLPSO and MIQCPs

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Abstract: Expansion of the e-commerce market due to the development of the Internet has increased in the volume of distribution, and the number of operations in distribution warehouses had also increased. Picking operation is one of the most important tasks, and companies are trying to make this task more efficient by introducing autonomous mobile robots (AMRs), which transports products manually picked to a depot. In this study, we propose a method to generate product assignments that make picking operations more efficient through a two-step optimization process. First, product assignments for utilizing AMRs are generated using particle swarm optimization. Next, in-shelf products layout is generated by mathematical optimization for the products group assigned to the shelves. In product placement optimization, one of the approximate solution methods of the metaheuristic, BLPSO, is fused with a class-based warehouse to obtain an optimal solution. In addition, the problem of in-shelf product layout is formulated in MIQCPs. The constraint expression is used to generate a layout that considers preventing picking mistakes and ensuring the safety of the picker. We have conducted placement optimization experiments using real-world logistic data and discuss the effectiveness of the proposed method.

1 INTRODUCTION

Logistics is an indispensable part of human life, and the development of e-commerce via the Internet has led to the sale and purchase of a variety of goods. As logistics volumes increase, large-scale logistics warehouses with high logistics efficiency are required. Logistics warehouses play a wide role as logistics bases; in particular, picking operations account for more than 50% of the total operational costs (Koster et al., 2007).

Many companies are trying to make picking operations more efficient by introducing low-cost Autonomous Mobile Robots (AMRs). AMRs are robots that move through a facility along a predetermined route and carry products that have been manually picked. They are easy to install and can also serve as unloading points (drop-off points) for products collected by pickers, allowing for more drop-off points. It is expected to reduce the travel distance required for picking. However, it is difficult to use AMRs to the fullest extent in existing product placement. In addition, in order to make practical use of product assignment that can take advantage of AMR, it is necessary to determine in-shelf product layout that can make manual picking operations safe and efficient. In this study, product placement is generated through a two-stage optimization process, shown in Figure 1, to make efficient manual picking operations possible. First, particle swarm optimization (PSO) generates product assignments to use AMRs to the fullest extent. Next, mixed integer quadratic constraints programmings (MIQCPs) is used to generate in-shelf product layouts for the product groups generated by product assignment optimization. For product assignment optimization, we use BLPSO, a combination of lévy flight and PSO. PSO is given four initial solutions: two class-based storage, current placement, and random placement, to compare picking costs before and after optimization. Two class-based storage takes into account two drop-off points and divides shelves into classes. In-shelf product layout optimization using mathematical optimization generates an in-shelf

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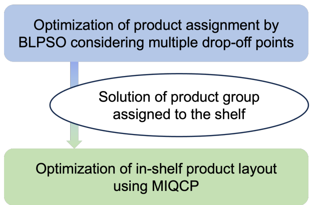
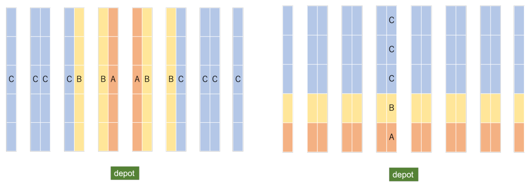


Figure 1: Overview of two-stage optimization.



(a) Placement with one class in each aisle. (b) Placement ordered by closeness to depot.

Figure 2: Example of shelf classifications.

product layout that considers picker safety by placing heavy product in the lower rows and efficiency by placing frequently shipped products in the middle rows. The generated in-shelf product layout and the value of the objective function are compared before and after optimization, and discussed the effectiveness. Section 2 describes the product assignment using PSO, and Section 3 presents the in-shelf product layout using MIQCPs in detail.

1.1 Related Work

With respect to the product-assignment problem, various methods exist for assigning storage space, and class-based storage is one of the most common methods (Koster et al., 2007). This method divides shelves and products into classes and randomly assigns them to the same class. Classes are often divided into three categories and products are classified according to their shipment frequency. Figures 2(a) and (b) show example of a shelf classification. Figure 2(a) shows a placement in which each aisle contains only one class, whereas Figure 2(b) shows a placement in which all shelves containing the products of each class are placed in the order of the nearest depot. These placements are simple, yet demonstrate high performance. However, class-based storage does not consider the combination of product orders or the distance traveled between products when picking multiple products in a sequence.

With respect to the in-shelf product layout problem, the facility layout problem (FLP) involves generating an optimal layout that ensures lower cost and more efficient production (Pérez-Gosende et al., 2021). The layout includes the floor plan of a house, the arrangement of rooms in the office, or even the arrangement of specific facilities, such as hospitals, in the entire city. Depending on the conditions defined, single-row facility layout problems (SRFLPs) (Meskar et al., 2020; Cravo and Amaral, 2019) and multi-row facility layout problems (MRFLPs) (Anjos and Vieira, 2021; Dahlbeck et al., 2020) exist, and these methods also vary (Hosseini-Nasab et al., 2018; Hungerländer and Rendl, 2013). Wu et al. (Wenming et al., 2018) formulated a problem using mixed integer quadratic programmings (MIQPs), one of the mathematical optimization, to generate floor plan candidates for open-field facility layout problems. The rooms were rectangular polygons optimized in a rectangular layout. Constraints such as rooms that do not overlap with each other and rooms placed within a boundary were expressed. Rectangles were combined by labeling to represent rooms with complex shapes, such as U- and L-shapes.

2 PRODUCT ASSIGNMENT PROBLEM BY BLPSO

Product assignment optimization is formulated as a combinatorial optimization problem. Because the number of product assignment combinations is large in the warehouses targeted in this study, metaheuristics were used to obtain approximate solutions. Watanabe et al. (Watanabe et al., 2021) proposed a system for product assignment optimization using BLPSO, a particle swarm optimization algorithm that incorporates lévy flight and is effective for high-dimensional problems. The system proposed by Watanabe et al. optimized the shelves to which products are assigned, evaluates the candidate solutions generated by the simulator, and updates the solutions. Experimental results showed that BLPSO produced better solutions than class-based storage, the current real warehouse placement. However, this system does not consider the installation of AMRs or multiple drop-off points. AMRs are assumed to be another drop-off point (AP, AMR Point) in addition to the conventional drop-off point (PS, Picking Station).

2.1 Settings

Set of shelves and products with $\boldsymbol{s} = [s_1, \ldots, s_{n_s}]$ and $\boldsymbol{m} = [m_1, \ldots, m_{n_m}]$, and we defined the decision variables as shelves $\boldsymbol{x} = [x_1, \ldots, x_{n_m}]$ where the products are stored. When $x_i = s_j$, product m_i is placed on shelf s_j. For order picking, a picking group (PG) is created based on the order sheet, which is a group of products to be picked in one trip. Pickers travel around the storage area to pick up products by following the PGs and deliver the collected items to the drop-off points (PS or AP) by each of the four PGs. In this study, the distance for picking all PGs $\boldsymbol{G} = [g_1, ..., g_{n_g}]$ was defined as picking cost and used as objective function. The objective function f was formulated as follows.

$$f(x) = distance(\boldsymbol{x}, \boldsymbol{G}), \tag{1}$$

where $distance(\boldsymbol{x}, \boldsymbol{G})$ indicates the total distance traveled by PG for the picking operation with respect to product placement $\boldsymbol{x}$. This includes the distance traveled to and from the drop-off points. The volume of shelf s_i was denoted by C_i, and the shelf-capacity constraint was formulated as follows:

$$C_i \geq v_i \quad (i = 1, ..., n_s), \tag{2}$$

$$v_i = \sum_{\{j | x_j = s_i\}} volume(m_j), \tag{3}$$

where v_i is the total volume of products placed on shelf s_i, and $volume(m_j)$ is the volume occupied by product m_j.

2.2 Proposed System

In the current product placement, frequently ordered products are often stored close to the PS because there was only one place to drop off the collected products. Therefore, we proposed a new product placement optimization system for efficient use of the AMR installed in existing warehouses by integrating previous research on class-based storage and the product assignment optimization method using PSO. First, one of the candidate solutions (product placement) generated by the PSO algorithm was initialized with a product placement created by referring to class-based storage. It aims to place the bestselling products near the AMR as well, and to optimize the placement. Initialization of the PSO solution is discussed below. The product assignment was then passed to the simulator, which was designed by following the actual picking method. In the simulator, order picking simulation and constraint calculation were conducted based on the order data in the product placement. Then, the algorithm updated the solution by considering the fitness evaluations. Additionally, cargo carts were used as the new drop-off point, and AMR was used to retrieve the cargo.

2.2.1 Updation of the Fitness Function Based on the Distance Traveled

In this system, the solution was evaluated as the expected value. The picking cost was defined as the collection and round-trip distances. The collection distance is the shortest distance between the products in PG, and the round-trip distance is the distance between the products and PS. The round-trip distance was evaluated based on the expected value. The fitness function f' was formulated as

$$f'(x) = \sum_{i}^{n_g} \{TSP(\boldsymbol{x}, \boldsymbol{g}_i) + \frac{1}{4}\overline{dist}(\boldsymbol{x}, \boldsymbol{g}_i) \times 2\}, \tag{4}$$

where $TSP(\boldsymbol{x}, \boldsymbol{g}_i)$ indicates the shortest distance for collecting all products in PG $\boldsymbol{g_i}$ at product placement $\boldsymbol{x}$ and is obtained by solving traveling salesman problem. Also, n_g denotes the total number of PGs, $\overline{dist}(\boldsymbol{x}, \boldsymbol{g}_i)$ denotes average distances between each drop-off points and products in $\boldsymbol{g}_i$ and was formulated as follows:

$$\begin{aligned}\overline{dist}(\boldsymbol{x}, \boldsymbol{g}_i) = &\frac{1}{2}\left\{\overline{outward}(\mathrm{PS}) + \overline{outward}(\mathrm{AP})\right\} \\ &+ \overline{return}(\mathrm{PS}, \mathrm{AP}),\end{aligned} \tag{5}$$

where $\overline{outward}(\mathrm{PS})$ and $\overline{outward}(\mathrm{AP})$ denote outward trip function which return the average distance between PS, AP and each products in $\boldsymbol{g}_i$, $\overline{return}(\mathrm{PS}, \mathrm{AP})$ denotes return trip function which returns the average distance between the nearest drop-off points (PS or AP) and each products in $\boldsymbol{g}_i$. The picker returns to the drop-off points after every 4PG.

2.2.2 Initialization of the Particle's Global Best Solutions

The initialization effect enables an efficient search in the warehouse assignment optimization problem in PSO-based optimization using hints to narrow the search range without losing the diversity of the initial population. In this study, multiple product placements were provided as the initial values of the global solution *gBest*, and the product assignment optimization problem was solved.

2.3 Particle Swarm Optimization

PSO is a stochastic optimization method based on swarm intelligence and a multi-point search strategy. Ihara et al. (Ihara et al., 2019) compared PSO with ε constrained genetic algorithm (εGA), one of a heuristic solution method, and confirmed that PSO is significant. Furthermore, Ihara and Kato (Ihara and Kato, 2020) proposed BLPSO, that extends binary-PSO (BPSO), which used bit strings as position vectors of particles in PSO, and improved the efficiency of the search by controlling the step size of sampling candidate solutions from the probability distribution represented by the position and velocity of particles by the lévy distribution. Lévy flight (Fogedby, 1994) is a Random Walk whose step length follows the lévy distribution. The combination of PSO and lévy flight was particularly effective when the number of dimensions of the decision variables and the possible values for each variable are large. This BLPSO was used to optimize product assignment.

3 IN-SHELF PRODUCT LAYOUT PROBLEM BY MIQCPS

The in-shelf product layout was formulated and optimized using MIQCPs, a mathematical optimization method. A typical problem in mathematical optimization is the knapsack problem. The problem is to maximize value or minimize cost under constraints such as capacity. Mathematical optimization problems are composed of constraints and objective functions, all of which are expressed in mathematical formulas. A problem in which both the objective function and the constraints are represented in nonlinear form is called an MIQCPs, which is an NP-hard problem.

3.1 Settings

Figure 3 shows the shelves used to solve this problem. The shelves have K rows, and a set of shelves consist of two shelves facing each other. The two shelves facing each other are represented by shelf 0 and shelf 1. Figure 4 shows the product configuration. The products are represented by rectangular polygons that are small boxes. One face is defined as the state when the small box is stored as long as possible in the height and depth directions. The number of faces is obtained from the number of small boxes stored. In addition, bulk bolts are particularly large and heavy. These products should be placed at lower row for safety during picking.

3.2 Formulation

It was formulated using an objective function and five liner and nonlinear constraints. The inputs were as follows:

W,H,D : indicate the width, height, and depth of the shelf.

w,h,d : indicate the width, height, and depth of the small box.

$weight$: indicates the weight of the small box.

SR : indicates the rank based on product shipping frequency. We ranked the number of shipments made in descending order, as calculated from the shipment records.

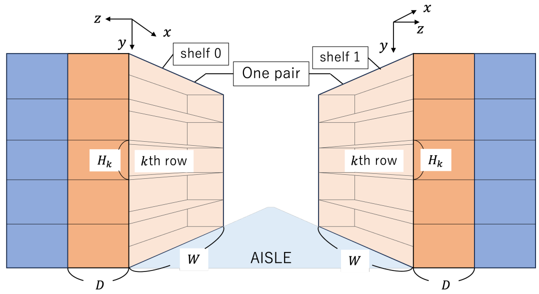


Figure 3: Settings and size of the shelf to be assumed for the real world situation($K = 5$).

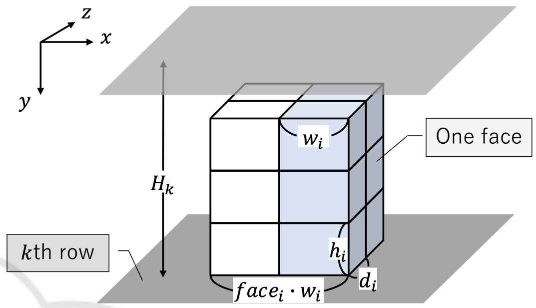


Figure 4: Description of product composition and face length.

n : indicates the number of boxes to be stored.

α : indicates a combination of similar products. α is represented by a binary value, and products i and j are similar when $\alpha_{i,j} = 1$.

β : indicates a bulk bolt. β is represented by a binary value, and the product i is a bulk bolt when $\beta_i = 1$.

A rectangle is represented by four parameters $(x, face, \varepsilon, \theta)$. x is the bottom-left corner x-coordinate of the rectangle, $face$ is the number of faces of the product, ε is the shelf of the rectangle is stored, and θ is the row where the product is stored. ε and θ are defined as a binary variable. These are subject to optimization. The constraints and objective functions are described in detail as follows:

Inside Constraints

To generate a valid layout, all the products must be placed inside the shelf. The x-coordinates of the four vertices of the rectangle representing the merchandise reside inside the shelf. This constraint was formulated as follows:

$$\begin{cases} \varepsilon_i \cdot W \leq x_i \leq (1+\varepsilon_i) \cdot W \\ \varepsilon_i \cdot W \leq x_i + face_i \cdot w_i \leq (1+\varepsilon_i) \cdot W, \end{cases} \quad (6)$$

where $1 \leq i \leq N$ denotes the number of products assigned to the shelf.

Face Length Constraints

Because the height of the rows varies, the number of faces and products that can be stored in the height direction varies depending on the row where the product is stored. Product i is placed in the kth row when $\theta_{i,k} = 1$. The face length constraint was formulated as follows:

$$face_i = \mathrm{round}(n_i, n_i') + 1, \tag{7}$$

$$n_i' = \mathrm{round}(H_k, h_i) \times \mathrm{round}(D, d_i), \tag{8}$$

where $\mathrm{round}(a,b)$ indicates the integer part of the a/b quotient, and $1 \le k \le K$ denotes the number of rows in the shelf.

Nonoverlap Constraints

The two rectangles have two directions: right, left, as determined by the auxiliary binary variable σ. Rectangle i exists to the right (left) of rectangle j when $\sigma^R_{i,j}\left(\sigma^L_{i,j}\right) = 1$. The nonoverlap constraint is formulated as follows:

$$\begin{cases} x_i \ge x_j + face_j \cdot w_j - M(1-\sigma^R_{i,j}) \\ x_i + face_i \cdot w_i \le x_j + M(1-\sigma^L_{i,j}), \end{cases} \tag{9}$$

$$\sum_{\substack{\{i,j|\theta_{i,k}=1\cap\theta_{j,k}=1\} \\ \{\gamma\in\{right,left\}\}}} \sigma^\gamma_{i,j} = 1, \tag{10}$$

where M is a large constant and $M = W \times D$. Then $\sigma^R_{i,j}\left(\sigma^L_{i,j}\right) = 0$, the first (second) inequality is always satisfied. Equation (10) ensures that one of the top two inequalities should be satisfied if product i and product j are same row. The auxiliary variable σ is automatically assigned during optimization, and this method is also used with other constraints.

Weight Constraints

To ensure picking safety, the rows in which heavy goods are stored must be limited. Bulk bolts should be placed in below the k'th row, and products other than bulk bolts with a weight of $Weight'$ or more should be placed in rows other than the 1st row. The weight constraint is formulated as follows:

$$\sum_{\substack{\{i|\beta_i=1\} \\ \{k'\ge k\ge K\}}}^{K} \theta_{i,k} = 1, \tag{11}$$

$$\sum_{\substack{\{i|weight_i'\ge Weight\} \\ \{2\ge k\ge K\}}}^{K} \theta_{i,k} = 1. \tag{12}$$

Nonadjacent Constraints

Similar products are placed separately to prevent mix-ups during the picking operation. Figure 5 shows the area in which adjacency is prohibited

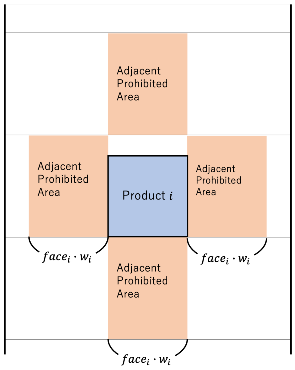


Figure 5: Description of the area where product i prohibits adjacency.

for product i. The non-adjacent constraint, expressed in terms of the auxiliary binary variable ρ, is formulated as follows:

$$\begin{cases} x_i \cdot \alpha_{i,j} \ge (x_j + 2face_j \cdot w_j - M\rho_{i,j}) \cdot \alpha_{i,j} \\ (x_i + 2face_i \cdot w_i) \cdot \alpha_{i,j} \le (x_j + M(1-\rho_{i,j})) \cdot \alpha_{i,j} \end{cases}$$
$$\{i,j|\theta_{i,k} = 1 \cap \theta_{j,k}\}, \tag{13}$$

$$\begin{cases} x_i \cdot \alpha_{i,j} \ge (x_j + face_j \cdot w_j - M\rho_{i,j}) \cdot \alpha_{i,j} \\ (x_i + face_i \cdot w_i) \cdot \alpha_{i,j} \le (x_j + M(1-\rho_{i,j})) \cdot \alpha_{i,j} \end{cases}$$
$$\{i,j|\theta_{i,k} = 1 \cap \theta_{j,k+1}\}. \tag{14}$$

Objective Function

The objective function defines that items with high shipment frequency are placed in the priority row and that heavy items are not placed in the 1st row. The objective function is expressed by assigning a penalty for disobedience. The objective function is defined as follows:

$$\min \quad \lambda(P_{shipment} + P_{width}) + (1-\lambda)P_{weight}, \tag{15}$$

where λ is the weight that controls the tradeoff between $(P_{shipment} + P_{width})$ and P_{weight}. The product with the large number of shipments is placed in the highest priority row. The order of priority is determined by *priority*. A penalty is assigned proportional to the rank of the number of products shipments and the priority of the row. $P_{shipment}$ is formulated as follows:

$$P_{shipment} = \sum_k \left(\sum_i (SR_i \cdot \theta_{i,priority_k} \times k) \right) \times \phi_1, \tag{16}$$

where $\phi = [\phi_1, \phi_2, \phi_3]$ is the weight that aligns the value range of the three penalties.

P_{width} is a penalty for placing more products in highest priority row. P_{width} is formulated as follows:

$$P_{width} = \left(2W - \sum_i face_i \cdot w_i \right) \cdot \theta_{i,priority_1} \times \phi_2. \tag{17}$$

P_{weight} is a penalty for the weight of the product and is applied when a heavier product weighing less than $Wight'$ is placed in the highest row. The penalty is proportional to the weight. P_{weight} is formulated as follows:

$$P_{weight} = \left(\sum_{i} (Weight_i \cdot \theta_{i,1}) \right) \times \phi_3. \quad (18)$$

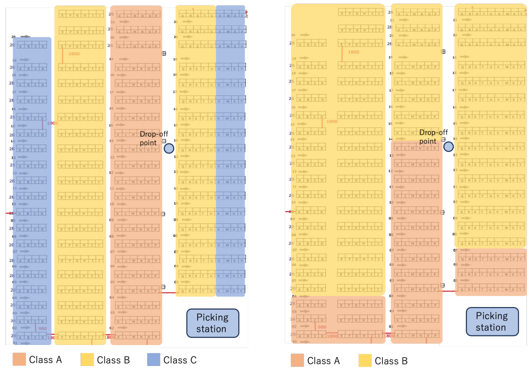
4 EXPERIMENTS

We experiment with product data from a logistics warehouse company. The in-shelf layout is optimized using the results of product assignment optimization. Product assignment is implemented in java, and in-shelf layout is implemented in Python using a solver "gurobi optimizer"(gur,). The CPU used in the experiments was AMD Ryzen Threadripper 3970X.

4.1 Experimental Setting

For product assignment optimization, the fitness function is optimized to minimize. No contingencies are considered in the simulation environment. Four different product assignments are assigned to the particles as the initial *gBest* of the PSO. Data were collected at logistic warehouse of collaborative company for three months (from December 1, 2021 to February 28, 2022), which was the experimental period. The ε-constraint method (Tetsuyuki Takahama, 2005) is employed to handle the capacity constraints. For the PSO parameters, the group size is set to 10, maximum number of iterations to 30,000, maximum velocity Vmax to 10.0, and the recommended value in (Kennedy and Eberhart, 1995). For the lévy flight, the scale parameters $\alpha = 1.0$ and $\beta = 1.5$ are set according to (Xin-She Yang, 2010). Four different initial solution *gBest* placements are given to the PSO particles. The current placement, within-aisle storage (WAS), two-class, and random placement. WAS and two-class classify the shelves into classes, as shown in the Figure 6. The total volume of shelves in each class is calculated, and products that fit in the volume are classified into the same class according to their order frequency. The shelves and products with matching classes in the current placement are unchanged. Products whose classes do not match are randomly assigned to shelves within the class.

The in-shelf product layout generates an in-shelf layout for each shelf based on the solution obtained from product assignment. Set parameters based on real world warehouse: the weight $\lambda = 0.3$ and $\phi = [0.001, 0.01, 0.0001]$ for the objective function. Assume that the number of rows $K = 5$, width $W = 820$, height $H = [365, 300, 300, 350, 360]$, depth $D = 480$, and $priority = [3, 2, 4, 5, 1]$. The parameter $Weight' = 4000$ [g] and $k' = 3$ for heavy products.



(a) Shelf classification of WAS. (b) Shelf classification of two-class.

Figure 6: Example of shelf classifications.

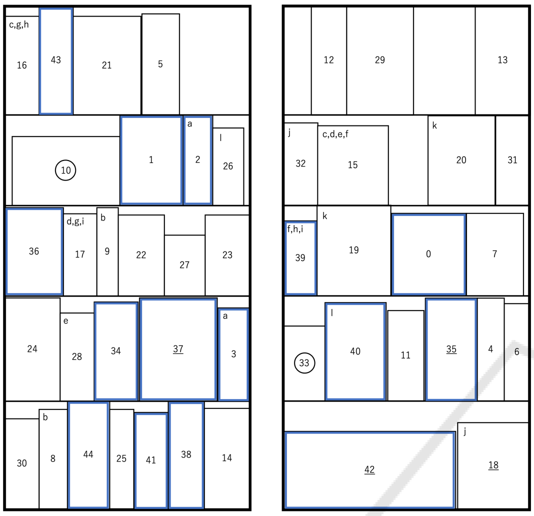
4.2 Experimental Results

Table 1 summarizes the results of product assignment, showing the picking cost (TSP), the distance from the drop-off point to the shelf, and the total distance before and after optimization for the four initial solutions *gBest*. In parentheses are the standard deviations. In the table, the picking cost TSP represents the shortest distance to collect all the products in the PG, and the drop-off to the shelf means the distance between each drop-off point and the products. The reduction from *gBest* is shown in terms of distance and percentage. The picking cost with the current placement is 1009.0 km, and the experiment with the current placement as the initial solution resulted in 965.1 km, a reduction of 43.8 km. On the other hand, for the class-based WAS and two-class, the initial placement costs were 853.4 km and 952.1 km. Both placements resulted in lower picking costs than the current placement optimization results. Furthermore, optimizing these two class-based storages further reduced the picking cost, resulting in a WAS of 845.1 km, the lowest cost among all methods. When the initial solution was random, the picking cost was large for the initial placement and was not as high as any of the methods when optimized. The reduction tended to be larger the larger the initial picking cost, and the maximum reduction was 4.3% when the current placement was used as the initial solution.

An example of the results generated by in-shelf product layout optimization based on the product groups determined by product assignment optimization is shown in the Figures 7(a) and (b). They show the results of in-shelf product layout for 45 products

Table 1: Experimental result of product assignment optimization (SD).

	Distance before optimization (km)			Distance after optimization (km)			Reduction	
	Total distance	TSP	Drop-off to shelf	Total distance	TSP	Drop-off to shelf	Distance (km)	Percentage (%)
Current	1009.0	809.7	199.2	965.1(4.48)	767.6	197.5	43.8	4.3(0.44)
WAS-stay	853.4	685.2	168.2	845.1(0.95)	677.1	168.0	8.3	0.97(0.11)
Two-class	952.1	763.7	188.4	939.6(1.57)	751.6	188.1	12.4	1.3(0.16)
Random	1149.3	944.4	205.0	1106.3(6.72)	903.0	203.3	43.0	3.7(0.59)



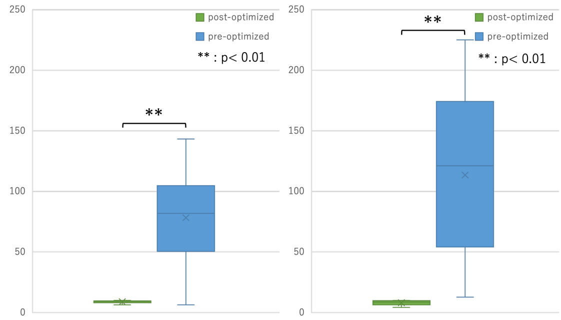
(a) shelf 0. (b) shelf 1.
Figure 7: Result of generating in-shelf product layouts for Shelf '12B05Q'.

for randomly selected in Shelf '12B05Q'. The numbers (0–44) indicate the index of 45 products, underlined numbers indicate bulk bolts, circled numbers indicate products weighing more than 4000 [g] other than bulk bolts, and the letters (a–j) in the upper left corner indicate pairs of similar products. Compared with the current layout, blue colored products (Product 0-3 and 35-44) indicate products that were assigned to '12B05Q' from other shelves by product assignment. Also, all 45 products assigned to '12B05Q' were changed to their optimal positions by in-shelf product layout optimization. The generated results satisfy all the constraints.

In addition, Figures 8(a) and (b) show the objective function values before and after optimization of the in-shelf layout for the 10 shelves closest to PS and AP. The average values for the 10 shelves near PS were 78.2 before and 8.8 after optimization, while the average values for the 10 shelves near AP were 113.5 before and 8.1 after optimization.

4.3 Discussion

The results in the Table 1 show that the TSP was reduced after product assignment optimization with

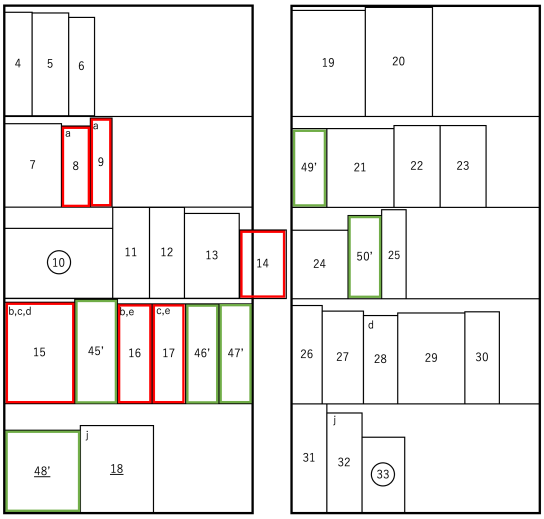


(a) 10 shelves near PS. (b) 10 shelves near AP.
Figure 8: Comparison of objective function values pre- and post-optimization.

BLPSO from the current arrangement. In particular, the TSP was the smallest when WAS was used as the initial solution. The combination of class-based and BLPSO produced the lowest cost product assignment. Figures 9(a) and (b) show the in-shelf product layout of '12B05Q' before optimization. Products colored green indicate products assigned to shelves other than '12B05Q' by the product assignment optimization. Products colored red are those that violate constraints. Product 14 is placed outside of the shelf and violates the inside constraint. Products 8, 9, 15, 16, and 17 violate the nonadjacent constraint. It can be said that in-shelf product layout optimization has generated an effective in-shelf product layout. In the comparison of the objective functions, the t-test confirmed a significant difference ($p < 0.01$) between the pre- and post-optimization results for the 10 shelves that are close to both PS and AP. In conclusion, the proposed method is effective and has potensial to generate feasible and efficient product layouts for picking operations.

5 CONCLUSION AND FUTURE WORK

We proposed the method for generating product assignments to make efficient manual picking operations in a distribution warehouse, which consists of two stages of optimization. First, PSO is used to generate a product assignment to maximize the utiliza-



(a) shelf 0. (b) shelf 1.

Figure 9: Pre-optimize in-shelf product layouts for Shelf '12B05Q'.

tion of AMRs. Based on the product assignments, in-shelf product layout is generated by mathematical optimization. The generated in-shelf product layout is an effective layout, which allows for more efficient and safer picking than the pre-optimized placement. In the future, we will investigate methods that allow interaction between the two optimization stages, such as performing multiple product assignment optimizations only on shelves where the objective function value is not improved, even though the two optimization stages are independent. We will also discuss the results of ongoing demonstration experiments using real-world logistic data.

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