

Pareto-Based Multi-Objective Optimization for Two-Block Class-Based Storage Warehouse Design

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ABSTRACT

This research proposes a Pareto-based multi-objective optimization approach to class-based storage warehouse design, considering a two-block warehouse that operates under the class-based storage policy in a low-level, picker-to-part and narrow aisle warehousing system. A mathematical model is formulated to determine the number of aisles, the length of aisle and the partial length of each pick aisle to allocate to each product class that minimizes the travel distance and maximizes the usable storage space. A solution approach based on multiple objective particle swarm optimization is proposed to find the Pareto front of the problems. Numerical examples are given to show how to apply the proposed algorithm. The results from the examples show that the proposed algorithm can provide design alternatives to conflicting warehouse design decisions.

Keywords: Warehouse Design, Multi-Objective, Two-Block Warehouse, Class-Based Storage Policy

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1. INTRODUCTION

The missions of a warehouse are storage and transport of goods in any configuration to the next link in the supply chain without damaging or altering the product's basic form (Garcia-Diaz and Smith, 2008). Effective warehouses can support the smooth material flows in the supply chain. The layout of warehouses is one of the many factors that affect the efficiency of the warehouse operations. The good warehouse layout may significantly help to reduce the average travel distance that can lead to the reduction of operating cost. In general, the layout problem within the warehouses is discussed based on a storage area that concerns aisle orientation, number, length, and width of aisle.

Multi-objective optimization considers two or more objectives simultaneously. In practice, most problems

contain multiple conflicting objectives; so multi-objective optimization is a very popular topic for researchers. In warehouse design, there are many objectives that should be considered such as minimizing travel distance, maximizing space utilization, and material accessibility.

This research proposes a mathematical model with multiple objectives for warehouse design problems that uses the class-based storage policy with two-block layout. In addition, a Pareto-based multi-objective optimization algorithm is applied to solve the mathematical model.

This article is divided into 6 sections. In Section 2, literatures about warehouse and multi-objective warehouse design are reviewed. In Section 3, a mathematical model is proposed. The Pareto-based multi-objective optimization is described in Section 4. Section 5 presents an example that shows how to use the proposed

algorithm. The summary is presented in the last section.

2. LITERATURE REVIEWS

In this section, the warehouse operation, warehouse design and multi-objective are reviewed.

2.1 Warehouse Operation

Warehouse operation may be divided into different phases. Larson *et al.* (1997) classify warehouse into three functions; receiving of goods from a source, storing of goods until customers order and the retrieving of goods when customers ordered. Generally, the main warehouse activities are receiving, storage, order picking/selection, and shipping.

2.1.1 Receiving and shipping

The two major traditional activities of a storage process are receiving (inbound operations) and shipping (outbound operations). Receiving operations move items from docks where they are unloaded to storage locations within a warehouse. Shipping operations move items from the storage location to the staging area where they will be loaded into the shipping vehicles, usually trucks and railroad cars. Both types of operations are significantly affected by the equipment selected and the movement pattern used to displace the products, either from the receiving docks to warehouses, or vice versa (Garcia-Diaz and Smith, 2008).

2.1.2 Storage

The main function of the warehouse is storage function that concerns with the organization of goods held in the warehouse. The objective of the storage function is either to maximize resource utilization while attempting to maximize customer satisfaction simultaneously. Therefore, in the design of warehousing systems, Tompkins *et al.* (1996) proposed the resource utilizations that should be maximized. The resource utilization may include space utilization, equipment utilization, labor utilization, material accessibility and material protection.

Three common storage policies that are used in the warehouse include random storage policy, dedicated storage policy and class-based storage policy. The *randomized storage policy*, also referred to as floating slot storage, allows the storage location for a particular product to change or float overtime. The advantages of this policy are the uniform utilization of the storage spaces and reduced aisle congestion (Petersen II, 1999). However, this policy has large travel times because the pickers must traverse the entire warehouse. The *dedicated storage policy* assigns each product to be stored at a fixed location. The advantage is that order pickers can remember the storage locations of items. However, the disadvantage of this policy is that it has the lowest space utilization among all storage policies. The class-based

storage policy is widely used in practice because it often leads to a substantial reduction in order pick travel distance when compared with random storage policy (Larson *et al.*, 1997; Onut *et al.*, 2008). This policy divides products into classes based on some criteria. The class-based storage policy distributes the products, based on their demand rates and the details are given by Van den Berg (1999). The area in the warehouse is divided and dedicated to each class. Storage within an area is random.

A random storage policy is the most common assumption that is often used during the design of warehouse layout (Gu *et al.*, 2010). However, the travel times of random storage policy are generally higher than those of other storage policies. The class-based storage policy is another storage policy with a good potential. It combines the benefits of both the dedicated storage policy and the random storage policy (Gu *et al.*, 2007) by dividing goods into classes based on some predefined criteria.

2.1.3 Order picking

Order picking is the process of selecting and retrieving specified items from a warehouse, in specified quantities, to satisfy a customer order. Order picking systems may be classified into three groups: picker-to-product systems, product-to-picker systems and picker-less systems. This article focuses on the picker-to-product system that the order picker walks or drives along the aisles to pick items on the pick cart. Routing policies determine the route of a picker for a picking tour, which specifies the sequence in which stock keeping units (SKUs) are to be picked. These policies range from simple heuristics to optimal procedures. *Traversal routing policy* is one of the simplest strategies for routing pickers in a warehouse where the picker enters and exits at opposite ends of each aisle and travels in a zig-zag manner along the aisle (Caron *et al.*, 1998, 2000; Petersen II, 1997, 1999; Petersen *et al.*, 2004). *The return policy* is the most popular alternative routing policy with the picker entering the aisle, picking on the right (left) shelf, turns at the furthest location to be visited and picking on the left (right) shelf while returning to the end of the aisle. A picker only enters those aisles containing picks (Petersen II, 1997; Hwang *et al.*, 2004). With random storage, the traversal policy always performs equal to or better than the basic return policy (Caron *et al.*, 1998). In *Midpoint policy*, each length of each picking aisle is divided into two equal parts at its midpoint. An order picker enters a picking aisle from a cross aisle, traverses only up to its midpoint to perform the picks in that section of the aisle, and returns to the same cross aisle. Depending on the items to be picked in an aisle, an order picker may have to enter the same picking aisle again from the other cross aisle (Hwang *et al.*, 2004). In *Largest gap return policy*, a picker enters an aisle only as far as the start of the largest gap within an aisle, instead of the midpoint. The largest gap represents the separation between any two adjacent picks, or between the central

across aisle and the first pick location, between the last pick location and the lateral cross aisle (Caron *et al.*, 1998; Petersen II, 1997, 1999). Peterson II (1997) described the *composite routing strategy* that combines the best features of the return policy and transversal routing policy. The composite strategy minimizes the travel distance between the farthest picks in two adjacent aisles.

2.2 Warehouse Design

Gu *et al.* (2007) divided the warehouse design decisions into five major decisions. First, the overall structure of a warehouse determines the material flow pattern, the department identification and the relative location of departments. Second, the sizing and dimensioning of the warehouse are determined. The size of the warehouse determines the storage capacity of a warehouse while the dimension translates capacity into floor space in order to assess construction and operating costs. Third, department layout decision concerns the detailed configuration within a warehouse department which includes pallet block-stacking pattern; aisle orientation; the number, length, and width of aisles; and door location. Fourth, the equipment selection determines the level of automation for the warehouse and addresses the storage equipment and material handling equipment. Finally, the operational strategies in the warehouse concern decisions in assigning items to storage and order picking strategies that may have global effects on operation performance. Therefore, the operational strategies need to be considered in the design phase. This article focuses on the third part which concerns the detailed configuration within a warehouse department.

There are many researchers working in the field of warehouse design that considers various storage policies. A random storage policy is the most common assumption that is often used during the design of warehouse layout (Gu *et al.*, 2010). There are fewer researchers that work with class-based storage policy when designing warehouse layout. An optimization procedure to aid a warehouse planner in the design of selected three dimensional palletized storage systems is developed by Park and Webster (1989a). Moreover, Park and Webster (1989b) proposed a “cubic in time” that is a new storage structure layout method for minimizing the travel time of selected handling equipment in a three dimensional palletized storage system. Larson *et al.* (1997) proposed a class-based storage procedure for warehouse layout. Practitioners of single-command lift truck pallet storage and retrieval are the target of this method. Three phases of the procedure were presented: determination of aisle layout and dimensions of storage zone, assignment of material to a storage medium, and allocation of floor space. A paper reel layout problem is considered by Lai *et al.* (2002). The problem considered different classes of paper reels that must be stored in the different cells of a warehouse. The objective is to minimize the transportation cost. The model is formulated but, unfortunately,

it is non-deterministic polynomial-time (NP)-hard and a simulated annealing method is proposed to solve the problem. Sooksakun *et al.* (2012) proposed a class-based storage warehouse design using a particle swarm optimization (PSO) algorithm. Single objective that is to minimize the travel distance for two-block warehouse is considered.

2.3 Multi-Objective Optimization

Multi-objective optimization considers more than one objective simultaneously. One of the most intuitive methods to solve multi-objective problem (MOP) is to convert it into a single objective problem. This method requires a set of weights based on the prior preference of the decision makers for each objective function. However, Kachitvichyanukul and Nguyen (2010) pointed out that this method has two important disadvantages. First, a single solution is obtained based on a set of pre-defined, subjective weights on the objective functions. Thus the requirement of prior preference of the decision makers may not lead to a satisfactory result. Second, the decision maker’s knowledge about the range of each objective value may be limited. As a result, even with a preference in mind, the single solution obtained provides no possibility for tradeoffs of decisions. In order to be more objective, the approach based on a single aggregative objective function needs to be run multiple times to see the effect of the weights on the solutions obtained. Nguyen and Kachitvichyanukul (2010) proposed a Pareto-based PSO algorithm for MOP that simultaneously minimizes a set of conflicting objective functions. The notations and mathematical model are given as follows:

Notations

- \vec{x} : the vector of decision variables
- K : the number of objective functions
- $f_i(\vec{x})$: the function of \vec{x}
- $g_i(\vec{x}), h_i(\vec{x})$: the constraint functions

Mathematical model for a minimization problem,

Objective

Minimize

$$f_i(\vec{x}) = [f_1(\vec{x}), f_2(\vec{x}), \dots, f_k(\vec{x})] \quad (1)$$

Subject to:

$$g_i(\vec{x}) \leq 0 \quad i = 1, 2, \dots, m \quad (2)$$

$$h_i(\vec{x}) = 0 \quad i = 1, 2, \dots, l \quad (3)$$

An illustration of non-dominated front is shown in Figure 1, given two solution vectors $\vec{x}, \vec{y} \in R^D$, the vector \vec{x} is considered to dominate vector \vec{y} (denote $\vec{x} \prec \vec{y}$), if $f_i(\vec{x}) \leq f_i(\vec{y})$ for $\forall_i = 1, 2, \dots, K$ and $\exists_j = 1, 2,$

..., $K | f_i(\bar{x}) < f_i(\bar{y})$. The quality of a solution in multi-objective is explained in terms of trade-offs that differ from single objective. For the cases that neither $\bar{x} \prec \bar{y}$ nor $\bar{y} \prec \bar{x}$, \bar{x} and \bar{y} are called non-dominated solutions or trade-off solutions. A non-dominated front N is defined as a set of non-dominated solutions if $\forall x \in N, \nexists y \in N | \bar{y} \prec \bar{x}$. A Pareto optimal front P is a non-dominated front which includes any solution \bar{x} that is non-dominated by any other $\bar{y} \in F, \bar{y} \neq \bar{x}$ where $F \in R^D$ is the feasible region.

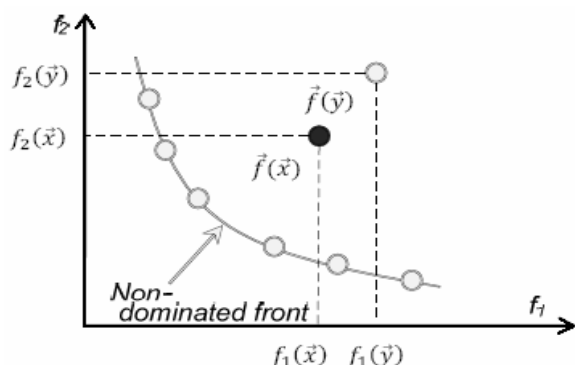


Figure 1. $\bar{x} \prec \bar{y}$ for case with two objectives.

A PSO framework for MOP is proposed by Kachitvichyanukul and Nguyen (2010). Figure 2 shows the PSO framework for MOP.

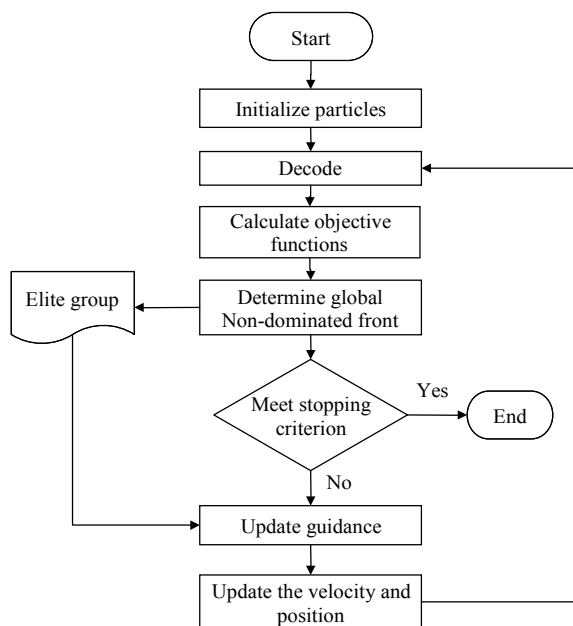


Figure 2. The particle swarm optimization framework for multi-objective problem.

There are few researchers that work on multi-objective optimization of warehouse. Poulos *et al.* (2001) solved the warehouse replenishment problem that is an MOP where various contradictory performance objec-

tives must be fulfilled. A special crossover operator in genetic algorithm (GA) was presented for determining the Pareto-optimal solutions in the warehouse replenishment problem. However, a disadvantage of the proposed algorithm is the appearance of unnecessary small displacements of products. Li *et al.* (2008) proposed a multi-objective mathematical model for storage location assignment. Two objectives are considered. First is to minimize the center of gravity of the rack. The other one is to minimize the total time. GA with Pareto-optimization and niche technique was developed to find optimal solution. To show the effect of the proposed algorithm, computational experience with randomly generated data sets and a case study are presented.

This research proposes a mathematical model for multi-objective warehouse design that considers space utilization and labor utilization. The space utilization is considered in terms of usable storage space that must be maximized. The labor utilization is considered in terms of the order travel distance that must be minimized. The mathematical model of the multi-objective warehouse design problem is given in the next section.

3. MATHEMATICAL MODEL

3.1 Notations

Indexes

- i : class index, $i = 1, 2, \dots, c$
- j : aisle index, $j = 1, 2, \dots, a$

Parameters

- q : number of picks in a picking tour
- c : number of classes
- w_a : width of the cross aisle
- w_b : center-to-center distance between two consecutive aisles
- w_c : width of the storage rack
- S : total floor space
- S_i : percentage of the total storage space used for class i
- f_i : percentage order frequency of product class i
- L_{min} : minimum length of a storage aisle
- u_0 : minimum percentage usable storage space of the warehouse
- TD : travel distance
- TD^{CA} : the cross-aisle travel distance
- TD^{WA} : the with-in aisle travel distance

Decision variables

- a : number of storage aisles
- L : length of a storage aisle
- l_{ij} : partial length of storage aisle j used for storing of product class i .

3.2 Assumptions

The mathematical models are formulated under the following assumptions (Figure 3):

- The total floor space of the warehouse is known.
- The warehouse consists of multiple identical rectangular racks. Each rack can be used to store more than one product type.
- The two-block warehouse layout is considered.
- The class-based storage and return routing strategy are used in this warehouse.
- Horizontal travel system, i.e., the picker moves only along the aisle floor (low-level system).
- The order pickers can pick items from both sides of the aisle by one pass; no addition time is needed for changing picking from one aisle side to the other, i.e., narrow aisle. Therefore, travel distances are measured along the aisle center line.
- Items in the same class have the same order frequency. The order frequency of each item-class is defined as the number of times that an item from that class is required in a planning period; it is known and constant throughout the planning period.

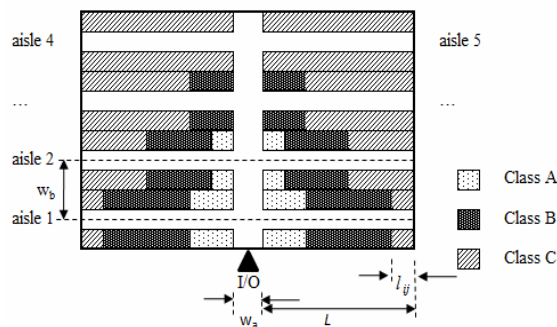


Figure 3. A warehouse with two-block layout.

3.3 Mathematical Model

Objective

$$\text{Minimize } TD = TD^{WA} + TD^{CA} \quad (4)$$

$$\text{Maximize } u = \frac{2wca}{S} \left[\frac{S}{aw_b} - \frac{w_a}{2} \right] \quad (5)$$

Subject to

$$2 \leq a \leq \left\lfloor \frac{2S}{(w_a + 2L_{min})w_b} \right\rfloor \quad (6)$$

$$\sum_{i=1}^c l_{ij} = \frac{S}{aw_b} - \frac{w_a}{2} \quad \forall j = 1, 2, \dots, a \quad (7)$$

$$\sum_{i=1}^c l_{ij} = S_i a \left[\frac{S}{aw_b} - \frac{w_a}{2} \right] \quad \forall i = 1, 2, \dots, c \quad (8)$$

$$l_{ij} = l_{ia-j+1} \quad \forall (i = 1, 2, \dots, c, j = 1, 2, \dots, a) \quad (9)$$

$$l_{ij} \geq 0 \quad \forall (i = 1, 2, \dots, c, j = 1, 2, \dots, a) \quad (10)$$

$$a \text{ is integer and even number} \quad (11)$$

Two objectives are considered in the mathematical model above. The first objective is to minimize the travel distance that shows in Eq. (4). The formulas for calculating the travel distances in the two-block warehouse with class-based storage policy were proposed by Le-Duc and De Koster (2005), and the formula for calculating the with-in aisle travel distance is presented in Eq. (12) followed by the formula for calculating the cross-aisle travel distance in Eq. (13).

$$TD^{WA} = 2 \sum_{j=1}^a \left\{ \left[\frac{w_a}{2} + (p'_{1j})q_j \frac{l_1 q_j}{q_j + 1} \right] \right. \\ \left. + \sum_{i=2}^c \left\{ \psi(p'_{ij}, q_j) \left[\sum_{k=1}^{i-1} l_{kj} \right. \right. \right. \\ \left. \left. \left. + \left(\frac{l_{ij} q_j p'_{ij}}{q_j p'_{ij} + \psi(p'_{ij}, q_j) \sum_{k=1}^i p'_{kj}} \right) \right] \right\} \right\} \\ \times \left[1 - \left(1 - \sum_{i=1}^c p_{ij} \right)^q \right]$$

where $p'_{ij} = \frac{p_{ij}}{\sum_{i=1}^c p_{ij}} (\forall j = 1, 2, \dots, a)$ and $\psi(p'_{ij}, q_j) =$

$$\left(\sum_{k=1}^i p'_{kj} \right)^{q_j} - \left(\sum_{k=1}^{i-1} p'_{kj} \right)^{q_j}, \quad i \geq 2$$

$$TD^{CA} = \sum_{j=1}^{\%2} \left\{ (2j-1)(w_b) \psi(n'_j, q) \right\} \quad (13)$$

where $n'_j = \frac{n_j}{\sum_{j=1}^{\%2} n_j}$ and $\psi(n'_j, q) = \left(\sum_{j=1}^j n'_j \right)^q - \left(\sum_{j=1}^{j-1} n'_j \right)^q$
 $(\forall j = 1, 2, \dots, \%2)$

The second objective is to maximize the usable storage space in the warehouse that is presented in Eq. (5). Eq. (6) presents the feasible range of the number of aisles. The aisle's length is shown in Eq. (7). Eq. (8) is the restriction on the total space for each class. Eq. (9) concerns the symmetrical property of the layout. In Eq. (10), the lengths of aisles are non-negative. Finally, Eq. (11) ensures that the number of aisle is an even integer number. A Pareto-based multi-objective optimization is proposed to solve the problem in the next section.

4. PARETO-BASED MULTI-OBJECTIVE OPTIMIZATION

The single objective PSO is extended by Nguyen and Kachitvichyanukul (2010), and the adapted flow-chart is given in Figure 4. First, the important input data for warehouse design are read into the program. Second, the maximum number of aisles is determined from the minimum length of an aisle. Third, a swarm of particles with $1 + \left\lfloor \frac{\text{Max. No. of Aisle}}{2} - 1 \times (\text{No. of Classes} - 1) \right\rfloor$ dimensions

is generated with random positions and zero velocity just like the regular PSO algorithm. The position of each particle is decoded into the number of aisle and the length of each pick aisle to allocate to each product class (see details in Section 4.1). All the particles are then evaluated for both objectives that are to minimize the travel distance and to maximize the usable storage space. At this point, all the particles are sorted and non-dominated solutions are identified. The set of non-dominated solutions will be updated and stored in the elite group. The elite group is also screened to eliminate any inferior solutions, i.e., solutions that were dominated by those in the elite group. The non-dominant particles in the elite group also serve the role of the global guidance for the movement of particles. If the stopping criterion is met, the procedure ends. Otherwise, the guidance is updated. The velocity and position of particles are updated based on the guidance, and the procedure is returned to the decode step to repeat the cycle.

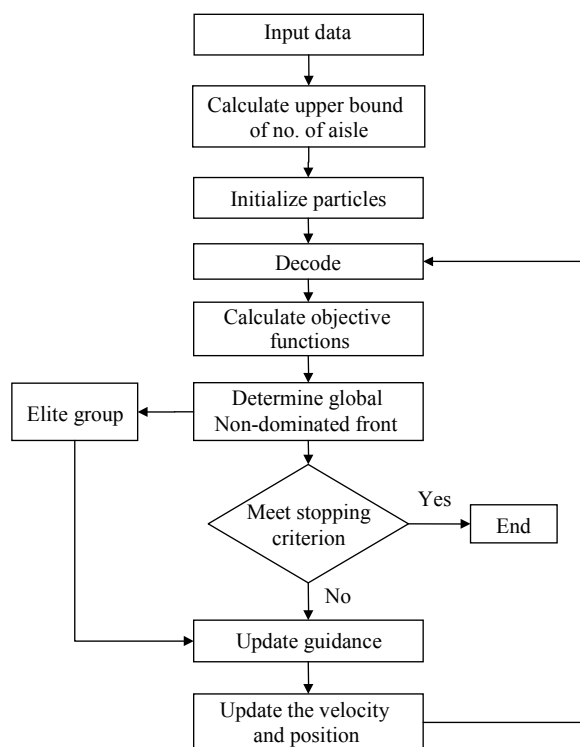


Figure 4. Pareto-based multi-objective optimization for warehouse design.

4.1 Solution Representations and Decoding Methods

The solution representation and the decoding procedure are discussed here. One of the key design variables is the number of aisles in the warehouse, and it can be any integer value between the minimum and maximum numbers of aisles. Given the maximum number of aisles and the number of storage classes, the dimensions of the particle for two-block warehouse is given in Eq. (14).

$$1 + \left\lceil \left(\frac{\text{Max. No. of Aisle}}{2} - 1 \right) \times (\text{No. of Classes} - 1) \right\rceil \quad (14)$$

Suppose that the maximum number of aisle in a two-block warehouse equals 12 and the number of product class equals three. The solution to this warehouse design problem can be represented as a particle with 11 dimensions as shown in Figure 5 where R_i represents a randomly generated value. An example particle with 11 dimensions is shown in Figure 6.

R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}	R_{11}
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Figure 5. A particle with 11 dimensions.

0.6	0.5	0.1	0.5	0.2	0.8	0.4	0.7	0.4	0.1	0.2
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Figure 6. An example of a randomly generated particle.

The first dimension represents the number of aisle by using Eq. (15).

$$\text{The number of aisle} = R_1(\text{Maximum no. of aisle}) - \text{Minimum no. of aisle} \quad (15)$$

The first dimension of the particle contains the value 0.6, and the value can be decoded into the number of aisles using Eq. (15). In this case, the number of aisles equals 6. Once the aisle is known; the length of aisle can be determined by using the formulas $L = \frac{S}{aw_b} - \frac{w_a}{2}$. The next dimensions are decoded to the partial aisle length for storage of items for each class. It is sufficient to decode only the partial aisle length of each class for the right hand side of the I/O point because the layout of the warehouse is symmetrical. Therefore, $li_j = l_{i,a-j+1}$.

5. ILLUSTRATIVE EXAMPLE

This section provides illustrative example for the multi-objective warehouse design.

The rectangular warehouse with narrow aisle is planned to store multiple product group. In addition, the order pickers can reach all items in the rack regardless of the rack's height; i.e., the vertical travel distance within the aisle is ignored. The warehouse is operated with a manual order picking system and the class-based storage policy. The general assumptions for the warehouse are:

- The warehouse size is designed for two-block warehouse that is 2,500 m².
- The width of the cross aisle is 2 m.
- The center-to-center distance between two pick aisles

- is 7 m.
- The width of the storage rack is 2.5 m. The minimum length of the storage rack is 10 m.
- The annual throughputs of the warehouse are classified into 4 groups; A, B, C, and D based on turnover frequency.
- The ordering probabilities of each class are 0.6, 0.25, 0.10, and 0.05, respectively. The percentage of the total storage space used for each class equal 20, 25, 25, and 30, respectively.
- In this research, the number of picks per tour equals 10.

Pareto-based multi-objective optimization for warehouse design is implemented in C# programming language using the MOPSO object library from ET-Lib (Nguyen, *et al.*, 2010). The parameters are set as follows. The number of particles is fixed at 100. Moreover, the stopping criterion is set at 200 iterations. The inertia weight is linearly decreasing from 0.9 to 0.4. The acceleration constants for self-learning and social learning are 1 and 1, respectively. In addition, the upper limit of elite group is fixed at 100 particles. Five replications are used in this experiment.

The necessary data for warehouse design are input to the program. After that, the solutions are collected. The results of the two-block warehouse are shown in Table 1 and Figure 5.

Table 1. Non-dominated solutions of two-block warehouse

The no. of aisle	Aisle length (m)	Travel distance (m)	Usable storage space (%)
2	177.571	403.284	71.029
4	88.286	308.920	70.629
6	58.524	259.457	70.229
8	43.643	236.370	69.829
10	34.714	223.253	69.429
12	28.762	218.682	69.029
14	24.510	218.438	68.629

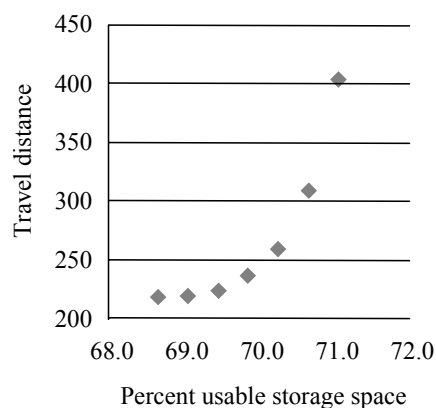


Figure 7. Non-dominated solutions of two-block warehouse.

Seven alternatives for the aisle layout are shown in Table 1. From Table 1, if the minimum number of aisle is selected for warehouse design, the percentage usable storage space is a maximum. The length of aisle is the longest. However, it has an effect on the travel distance which means that the travel distance is increased.

In Figure 7, if the maximum percentage usable storage space is selected, the increasing travel distance is 45.8% from minimum travel distance. Otherwise, if the minimum travel distance is selected, the usable storage space will reduced only 3.5%.

6. CONCLUSION

This paper presents a multi-objective mathematical model for a two-block warehouse layout design that uses the class-based storage policy. There are three decision variables: the number of aisles, the length of aisle and the length of each pick aisle to allocate to each product class. Moreover, Pareto-based multi-objective PSO is applied to solve the mathematical model. The proposed algorithm is capable of providing the alternative solution. The numerical example is given and the results from the example show that the proposed algorithm can provide design alternatives for the decision. There are many objectives when a warehouse is designed but this paper considers only two objectives. Therefore, it has room to improve the mathematical model.

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