MULTI-OBJECTIVE EVOLUTIONARY ALGORITHMS OF CORRELATED STORAGE ASSIGNMENT STRATEGY

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ABSTRACT
The traditional research on storage assignment strategies mostly concerns the single-objective optimisation problem (SOP) of travel distance in order-picking systems, in spite of diverse criteria. Considering the correlation between stock-keeping units, this paper presents multi-objective evolutionary algorithms of correlated storage assignment strategy for the multi-objective optimisation problems (MOP). Two types of objectives are considered. One is time consumption, consisting of travel time (converted from travel distance) and pick time, implying the MOP into SOP. The other is a parallel convergence of time consumption and energy expenditure. The multi-objective insertion and exchange algorithms are developed, and further improved through a skip method. After that, a model for a single-block warehouse with four routing strategies is built in Matlab to evaluate these algorithms. The experiment shows that the correlated storage assignment strategy can improve multiple objectives, by comparing with the full-turnover strategy.

Keywords: order-picking, correlated storage assignment strategy, multi-objective evolutionary algorithm

1. INTRODUCTION

Order-picking is a highly time-consuming and labour-intensive activity in warehouse management. Starting at the depot with a picking order of stock-keeping units (SKUs), quantity, and pick positions, the order-picker travels in a warehouse, collects SKUs in the racks and takes them back to the depot. This activity accounts for as much as about 55% of warehousing costs (Koster, Le-Duc, and Roodbergen 2007), so the storage location assignment plays a very important role in the warehouse operations.

Given a low-level, one-block, picker-to-parts order-picking system with SKUs, two problems are considered: how to assign the SKUs to the storage locations and how to determine the travel route of the order-picker. Both of them directly affect the efficiency of warehouse operation. Nevertheless, Frazelle (1989b) proved the storage location assignment problem to be non-deterministic polynomial-time hard (NP-hard), and the shortest route was frequently studied as the travelling salesman (TSP) problem in graph theory. In fact, the travel route is just one special case of it (Jünger, Reinelt, and Rinaldi 1995). The Hamiltonian cycle problem was proved to be NP-complete (Karp 1972), implying the TSP problem was typically NP-hard (Glover and Kochenberger 2006). As a result, diverse storage assignment strategies and routing strategies are developed heuristically to obtain practical solutions to the warehouse management problem.

For the storage location assignment problem (SLAP), Koster, Le-Duc, and Roodbergen (2007) stated that five types of storage assignment policies were usually used: random storage, closest open-location storage, dedicated storage, full-turnover storage, and class-based storage. However, Van Den Berg (1999) pointed out that randomised and dedicated storage policies are actually extreme cases of the class-based storage policy, because all the SKUs can be seen as one class by the randomised storage, whilst each SKU is seen as one class by the dedicated storage. The picking frequency and the cube-per-order index (COI, Heskett 1963) are often applied by the full-turnover strategy. In addition to picking frequency, the COI also takes the volume of SKUs into consideration.

Moreover, the correlation between SKUs in the picking orders was further studied to develop correlated storage assignment strategies (CSAS). Frazelle and Sharp (1989a) formulated this problem into a correlated assignment strategy, and conveyed that this strategy can achieve the same goal, instead of hiring more workers and improving the additional hardware. After that, Frazelle (1989b) developed the CFZS (cluster first, zone second) procedure. The non-complementarity measure between two SKUs was used to formulate the correlated storage assignment strategy as a p-median problem (Rosenwein 1994).

Amirhosseini and Sharp (1996) stated that six measures could be used to describe the correlation. Bernnat and Isermann (1998) developed the “easy sequencing heuristics” by means of an analysis of the correlation between SKUs in matrix, using a threshold to limit the correlation between SKUs in itemsets. Liu (1999) combined the clustering of SKUs and the sequence of picking lists and developed a zero-one integer programming model.

Mantel, Schuur, and Heragu (2007) developed order-orientated slotting for S-shape and vertical lift modules, presenting an interaction-frequency-based quadratic assignment heuristic, but it is also an NP-hard combinational optimisation problem, and very difficult to find the exact solutions (Sahni and Gonzalez 1976). The cluster-based rule and the cluster-based and turn rule were developed for the establishment of the priority list (Bindi, Manzini, Pareschi, and Regattieri 2009). Based on a mathematical model and two direct heuristics, two hybrid genetic algorithms with different crossover mechanisms were presented (Xiao and Zheng 2012).

Chiang, Lin, and Chen (2014) presented the modified class-based heuristic and the association seed-based heuristic based on the weighted support count, testing them with the S-shape strategy. With the precondition that each column/bay contained only a single SKU, a two-phase solution heuristic was presented, consisting of a minimum delay algorithm and a layout generation (Wutthisirisart, Noble, and Chang 2015). Zhang (2016) presented a methodology to develop the algorithms of the correlated storage assignment strategies, and developed sum-seed clustering and static-seed clustering to mine itemsets, four ways of sorting itemsets and single SKUs, and the insertion algorithm.

In the travelling salesman problem, a salesman travels from his home city, visits all the other cities on the list only once, and finally returns to his home city. To finish this work as soon as possible, the shortest route has to be found. Although Little, Murty, Sweeney, and Karel (1963) developed the branch-and-bound method to reduce the search time for the optimum route, the calculation time grows exponentially. The calculation is still extremely time-consuming when there are too many cities. In order-picking, the depot and all the picking positions in one picking order can be seen as “cities” in the travelling salesman problem.

Due to the difficulty of the search for optimum routes, numerous routing strategies are heuristically developed to provide both economical and practical solutions. Roodbergen (2001) presented five heuristic routings of order-pickers: S-shape, return, midpoint, largest gap, and combined, and the order-picking could be either single-sided or double-sided. Hompel, Sadowsky, and Beck (2011) discussed the S-shape strategy with/without skip and single-sided/double-sided return strategy further. Sadowsky (2007) developed formulas for calculating travel distance under single-sided and double-sided return strategies, midpoint strategy, as well as S-shape strategies with and without skip, based on a certain picking probability distribution of SKUs. In fact, the picking probability distribution of SKUs is very complex and dynamic, but little research was done on the travel distance calculation of actual picking orders under diverse routing strategies.

Since travel distance has a great effect on the productivity of order-picking, the reduction in travel distance was often set as an optimisation goal of order-picking systems. However, past research has been limited to single-objective optimisation problems, and more criteria should be considered in the optimisation of order-picking systems.

Multi-objective optimisation is a common problem in diverse fields of science and engineering. It deals with a simultaneous optimisation of multiple criteria, which may be in conflict with each other. A usual way was to weigh the priority of the criteria, so that MOP could be converted into a single-objective problem (Sooksaksun 2012). However, the weights were subjectively pre-defined, and the objective values range was perhaps limited, which meant that the decision-maker could only get a little information about potential trade-offs through this simple solution (Nguyen and Kachitvichyanukul 2010).

In the past decades, MOP has been studied a lot in enormous fields and a vast array of algorithms has been developed. The multi-objective evolutionary algorithms (MOEA) were considered as a feasible solution to MOP, because a set of representative Pareto optimum solutions could be found in a single run (Ding and Wang 2013).

However, MOP and MOEA have seldom been applied in warehouse management research. Molnar and Lipovszki (2002) presented a genetic algorithm with Pareto elitist-based selection to optimise the routing and scheduling of order-pickers in a warehouse, considering time constrain, labour and earliness/tardiness penalty costs. Önüt, Tuzkaya, and Doğaç (2008) developed a particle swarm optimisation algorithm to search for the optimum layout, as regards the classified products by turnover rates. Sooksaksun (2012) proposed a Pareto-based multi-objective optimisation approach to minimise the travel distance and maximise the usable storage space, using the number of aisles, the length of the aisles, and the partial length of each pick aisle as variables. He also studied the Pareto front of the problems by multiple objective particle swarm optimisation.

In this paper, the correlation between SKUs has been considered in order to optimise the storage location assignment problem in respect of multiple objectives, including the travel distance, pick time and energy expenditure of the order-picker. The correlated storage assignment strategy has been further developed with multi-objective evolutionary algorithms to obtain feasible solutions.

The remainder of this study is shown as follows: Section 2 presents a mathematical model; Section 3 concerns algorithms; Section 4 shows a modelling in Matlab; Section 5 develops methods of calculation; Section 6 deals with an experiment, whilst Section 7 concludes the study.

2. MATHEMATICAL MODEL

In this section, a mathematical model is presented for the multi-objective optimisation problem of storage location assignment. Section 2.1 shows the notations. Section 2.2 presents the assumptions, whilst Section 2.3 describes the problem.

2.1. Notations

An xyz coordinate system is established for the warehouse's storage locations, using x for the number of columns, y for the number of rows and z for the number of racks. The storage location in the first row of the first column of the first rack is set as the origin. The following notations are used to formulate the mathematical model.

Table 1: Notation

Variable	Description
$a_{d,l}$	Boolean variable
a_w	Width of pick aisle
$b_{d,l}$	Boolean variable
b_w	Half-width of cross aisle
d	Number of pick aisles (from left to right)
$d_{\max,l}$	Number of the rightmost pick aisle with pick positions of picking order l
$d_{\min,l}$	Number of the leftmost pick aisle with pick positions of picking order l
k_l	Number of travelled pick aisles of picking order l
k_p	Weight of energy expenditure for picking
k_t	Weight of energy expenditure for travelling
$l = 1, 2, \cdots, L$	ID of picking order
l_c	Width of a pick aisle and two racks
l_p	Length of a pick aisle and width of a cross aisle
n_x	Total number of columns
n_y	Total number of rows
n_z	Total number of racks
$p = 1, 2, \cdots, H$	ID of SKU
$q = 1, 2, \cdots, H$	ID of storage location
$t_{d,l}$	Boolean variable
$t_{z,l}$	Boolean variable
u_l	Length of storage location
u_w	Width of storage location
v	Travel speed of order-picker
$x_{a,d}$	x value of the last pick position in pick aisle d of UP
$x_{b,d}$	x value of the last pick position in pick aisle d of LP
$x_{d,l}$	x value of the last pick position in pick aisle d of picking order l under RB
x_s	x value of the last pick position of picking order l under SB
$x_{z,l}$	x value of the last pick position in rack z of picking order l under RS
z_l	Number of the last rack of picking order l
S_l	Travel distance of picking order l
F	Assignment matrix
G	SKU priority list

2.2. Assumptions

An actual order-picking system is extremely complex with numerous changeable conditions, but the prerequisite of an optimisation is the definiteness of every factor and parameter. To develop algorithms of an optimisation, assumptions have to be made to limit order-picking systems into a mathematical model. In this study, the order-picking system is analysed under the following assumptions.

1. The warehouse has one block, with all racks placed in parallel, see Figure 1.
2. The depot locates at the first corner of the first cross aisle and the first pick aisle.
3. Only one order-picker is responsible for the warehouse, and works in the picker-to-parts way.
4. The storage locations have the same length, width and height.
5. The number of SKUs is the same as the warehouse storage capacity.
6. Each SKU has a unique storage location.
7. SKUs of the same column in a rack are stored decreasingly by picking frequency in storage locations which are sequenced increasingly by pick time.
8. The order-picker moves at a constant speed.
9. The time consumption of the order-picker is stable for the same vertical position in the columns, whilst picking up SKUs and putting them in the picking cart.

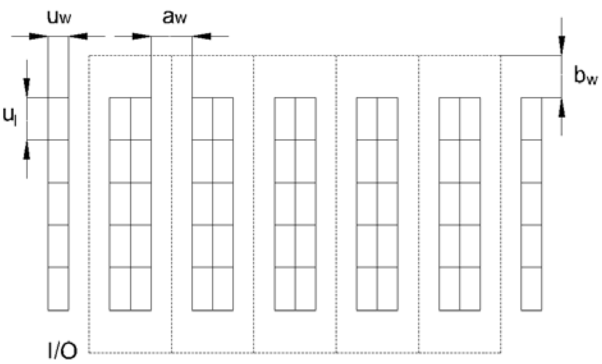

Figure 1: Warehouse Layout

2.3. Problem description

The storage location assignment is a combinational problem of SKUs and storage locations. Given a warehouse with H storage locations and H SKUs, an assignment matrix **F** is used to describe the exact assignment plan. The row numbers and column numbers of **F** match the ID of SKUs and storage locations respectively. If SKU p is stored in the storage location q, let $\mathbf{F}(p,q)$ equal to 1, otherwise 0. The row vector **G** with H elements stands for the SKU priority list. The ID of SKUs for each storage location is saved as the corresponding element of $\mathbf{G}$. The function $f_n(\mathbf{G})$ presents the diverse objective functions of the optimisation. With a certain routing strategy as a precondition, a general mathematical model of this multi-objective problem for the storage location assignment is summarised in the following:

$$\min F(\mathbf{G}) = (\mathrm{f}_1(\mathbf{G}), \cdots, \mathrm{f}_n(\mathbf{G}))$$
$$\text{s. t. } \begin{cases} \sum_{p=1}^{H} \mathbf{F}(p,q) = 1,\ \mathrm{q} = 1, 2, \cdots H \\ \sum_{q=1}^{H} \mathbf{F}(p,q) = 1,\ \mathrm{p} = 1, 2, \cdots H \\ \sum_{p=1}^{H} \sum_{q=1}^{H} \mathbf{F}(p,q) = H \end{cases} \tag{1}$$

Travel distance is often used as a criterion of the single-objective optimisation. For simplification, the travel speed of the order-picker is usually set as a constant. As a result, the minimisation of travel distance can be converted into the minimisation of travel time, so that travel time and pick time can be added together, and this multi-objective optimisation problem is turned into a single-objective optimisation problem. Set $\mathrm{f}_t(\mathbf{G})$ as the objective function of travel time, and $\mathrm{f}_p(\mathbf{G})$ as the objective function of pick time. The converted single-objective function (CSF) is presented as followed:

$$\min F(\mathbf{G}) = \mathrm{f_t}(\mathbf{G}) + \mathrm{f_p}(\mathbf{G}) \tag{2}$$

In contrast, the unit of energy expenditure is different to that of time consumption. Theoretically, they can be weighted to get the weighted product as the objective. However, this method makes little sense when optimising order-picking systems, as the weights are defined empirically. A heuristic approach is to simultaneously search convergent solutions of time consumption and energy expenditure. Set $\mathrm{f}_{te}(\mathbf{G})$ as the energy expenditure of travelling and $\mathrm{f}_{pe}(\mathbf{G})$ as the energy expenditure of picking. Considering the three criteria together, the multi-objective function (MF) is further developed:

$$\min F(\mathbf{G}) = ((\mathrm{f_t}(\mathbf{G}) + \mathrm{f_p}(\mathbf{G}), \mathrm{f_{te}}(\mathbf{G}) + \mathrm{f_{pe}}(\mathbf{G})) \tag{3}$$

Compared with the single objective optimisation of the storage location assignment problem, which is NP-hard (Frazelle 1989b), this model is more complex, and it is more difficult to find optimum solutions. Practically, an SKU priority list and a storage location list are usually formed and then merged together, to complete the storage location assignment problem. As a result, algorithms have to be developed to obtain the two lists.

On the one hand, algorithms for the storage location list are determined by routing strategies. It is relatively easy to present heuristic methods for it. With the S-shape strategy, the SKUs are usually stored from the depot in the racks of the first pick aisle, and then change the direction in the next pick aisle, just like an S-shape. With the double-sided return strategy, the assignment is always carried on from the bottom to the top in each pick aisle and the sequence of pick aisles is from left to right (Zhang 2016). Different to this is the single-sided return strategy, where the SKUs are assigned to storage locations of each rack from bottom to top and from left to right. The heuristics of the midpoint strategy are more complex: the SKUs are firstly assigned to storage locations in the first pick aisle, then the lower half of the rest of the pick aisles from bottom to top and from left to right and, finally, in the upper half of the rest pick aisles from top to bottom and from left to right.

On the other hand, heuristic algorithms for the SKU priority list are more complex, because they are deeply affected by the structure of picking orders. Thus, feasible algorithms need to be developed for these optimisation problems.

3. MULTI-OBJECTIVE EVOLUTIONARY ALGORITHMS

Based on the objective functions of the mathematical model in Section 2, multi-objective evolutionary algorithms are developed in this Section. These algorithms progressively approach the optimum solution to the storage location assignment problem, scanning all the SKUs.

Different to the common application of genetic algorithms, which exchange the positions of items in the sequence and treat them equally, the priority of storage locations must be taken into consideration when developing algorithms for the storage location assignment problem, because of the various travel distances between the depot and storage locations.

Due to the complex correlation between SKUs in the order structure, if the assignment of multiple SKUs is changed simultaneously, the effect on the objective function will be greater. To approach the optimum solution step-by-step, the insertion algorithm (Zhang 2016), which considers improvement by single positions, can be adapted for these multi-objective optimisation problems of storage location assignment, considering the correlations of SKUs to find convergent solutions. The result of the full-turnover storage is used as the object to be improved, to provide a better initial solution, and the number of correlated SKUs for the scanned SKU is limited to an experimental threshold to avoid unnecessary calculation. The following processes present the multi-objective insertion algorithm (MIA):

1. Use the decreasing sequence of SKUs by picking frequency as the original SKU priority list.
2. Scan the SKU in the first position of the original SKU priority list and find its correlated SKUs to the right of it in the original SKU priority list, calculate their correlation values.
3. Save the correlated SKUs and the correlation

values in the first and second columns of a matrix, and decreasingly sort the rows based on the value in the second column.

4. Try each correlated SKU in this new order: take each of them out and insert them in the SKU priority list after the scanned SKU. If the objective function converges, replace this original SKU priority list with the new one, and scan the next position in the original SKU priority list. Otherwise, continue with the next correlated SKU.
5. If no improvement can be found within the experimental threshold of the number of the correlated SKUs, scan the next position in the SKU priority list as the processes (2-5).

Another option for the approach to the optimum solution is the multi-objective exchange algorithm (MEA). Instead of taking a correlated SKU out and inserting it after the scanned SKU, this method exchanges the storage locations of the SKU after the scanned SKU and the correlated SKUs, in order to seek out a better performance of the objective function. The steps (1-3 and 5) are the same as before, but step 4 is different:

4. Try each correlated SKU in this new order: exchange the storage locations of the SKU after the scanned SKU and the correlated SKU. If the objective function converges, save this new SKU priority list as the original one, and scan the next position in the original SKU priority list. Otherwise, go on with next correlated SKU.

However, these algorithms can be further improved. A skip method is used to improve their efficiency: if the correlated SKU is in the same column of the rack with the scanned SKU, skip it. In this way, the multi-objective insertion algorithm with skip (MIAS) and the multi-objective exchange algorithm with skip (MEAS) are further developed.

4. MODELLING IN MATLAB

To evaluate these multi-objective evolutionary algorithms of a correlated storage assignment strategy, a model is established in Matlab with a practical interface, in which all the parameters of the picking orders, layout and algorithms, as well as the experiment plan, can be defined.
Four modules are included in this model. The first module presents the generation of picking orders, based on five assumptions about the proportion and distribution of SKUs (Zhang 2016); the second module deals with the order analysis to calculate picking and correlation frequencies; the third module includes all the algorithms; the last one is responsible for the calculation of diverse objectives: travel distance, travel time, pick time, and energy. See Figure 2.

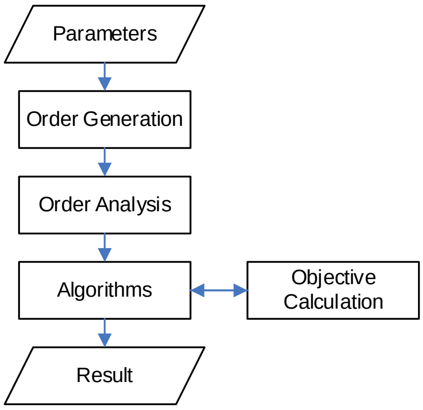

Figure 2: Modules in Matlab

To continue this model, five procedures are undertaken: firstly, set up variables and experiment plans; then, run the pre-calculation to initialise the parameters; next, run the calculation of diverse algorithms; lastly, the result is analysed, saving the outcome in Excel. See Figure 3.

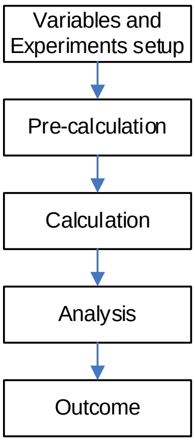

Figure 3: Implementation Procedures

5. METHODS OF CALCULATION

This section presents the formulas for the calculation of the objective functions, including travel distance, time consumption and energy expenditure.

5.1. Travel distance calculation

The travel distance of order-picking is significantly affected by routing strategies. In this study, the S-shape strategy (SB), the single-sided return strategy (RS), the double-sided return strategy (RB) and the midpoint strategy (MB) are considered in the experiment, and the travel distance is calculated per picking order and finally added up. The movement of the order-picker can be classified into two types: movement in pick aisles and cross aisles.

let $l_c = 2u_w + a_w$ and $l_p = 2b_w + u_l n_x$.

5.1.1. Travel distance of SB

The S-shape strategy offers two possibilities in which the number of travelled pick aisles k_l in picking order l is odd or even.

$$S_l = \begin{cases} 2l_c(d_{\max,l}-1)+l_p k_l, \text{ if } k_l \text{ is even;} \\ 2l_c(d_{\max,l}-1)+l_p(k_l-1)+2(b_w+u_1(x_s\text{-}0.5)), \\ \quad \text{otherwise.} \end{cases} \quad (4)$$

5.1.2. Travel distance of RS

In this case, there are two pick paths in a pick aisle, and each of them is for the rack next to it. So, the total width of pick aisle is set as $2a_w$ for the double-sided return strategy.

$$S_l = \begin{cases} 2(2(u_w+a_w)(\lfloor (z_l+1)/2 \rfloor -1)+a_w) \\ \quad +\sum_{z=1}^{z_l} t_{z,l}(b_w+u_1(x_{z,l}-0.5))), \text{ if } z_l \text{ is even;} \\ 4(u_w+a_w)(\lfloor (z_l+1)/2 \rfloor -1) \\ \quad +\sum_{z=1}^{z_l} t_{z,l}(b_w+u_1(x_{z,l}-0.5))), \text{ otherwise.} \end{cases} \quad (5)$$

$$t_{z,l} = \begin{cases} 1, \text{ rack } z \text{ has pick positions of order } l; \\ 0, \text{ otherwise.} \end{cases}$$

5.1.3. Travel distance of RB (Zhang 2016)

$$S_l = 2(l_c(d_{\max,l}-1)+\sum_{d=1}^{d_{\max,l}} t_{d,l}(b_w+u_1(x_{d,l}-0.5)))$$
$$t_{d,l} = \begin{cases} 1, \text{ pick aisle } d \text{ has pick positions of order } l; \\ 0, \text{ otherwise.} \end{cases} \quad (6)$$

5.1.4. Travel distance of MB

The midpoint strategy is a variant of the double-sided return strategy. It divides the whole warehouse into the upper part (UP) and the lower part (LP). If no more than one pick aisle in the upper part has pick positions, the division of the warehouse is no longer sensible, and the double-sided return strategy is more probable for this situation. Otherwise, the order-picker goes through the first pick aisle with pick positions, then picks up the rest of SKUs firstly in the upper part, and then in the lower part.

$$S_l = \begin{cases} 2(l_c(d_{\max,l}-1)+l_p+\sum_{d=d_{\min,l}+1}^{d_{\max,l}-1} a_{d,l}(b_w+u_1(x_{a,d} \\ \quad -0.5)+b_{d,l}(b_w+u_1(n_x-x_{b,d}+0.5))), \\ \quad \text{if } d_{\max,l}-d_{\min,l}>1; \\ 2(l_c(d_{\max,l}-1)+l_p), \text{ otherwise.} \end{cases}$$

$$a_{d,l} = \begin{cases} 1, \text{ pick aisle } d \text{ in LP has pick positions} \\ \quad \text{of order } l; \\ 0, \text{ otherwise.} \end{cases} \quad (7)$$

$$b_{d,l} = \begin{cases} 1, \text{ pick aisle } d \text{ in UP has pick positions} \\ \quad \text{of order } l; \\ 0, \text{ otherwise.} \end{cases}$$

Finally, sum S_l as $f_t(\mathbf{G})$.

5.2. Time consumption calculation

The travel time can be easily calculated by $f_t(\mathbf{G})/v$. However, the pick time depends on numerous factors, such as the stature of the order-picker, the height of the rack and the weight of the SKUs. For simplification of the mathematical model, the 9th assumption is made to reduce the number of factors in this study. The modular arrangement of the predetermined time standard (MODAPTS) is used to analyse the body movement of picking up SKUs in the different storage locations of the columns, so that the pick time can be quantified. For each picking order, SKUs with the same vertical positions are firstly counted up in order to calculate the weighted sum of pick time. Assuming that a rack has five rows, numbering from bottom to top, the analysis of pick time by MODFAPTS is shown in Table 2.

Table 2: Analysis of Pick Time by MODAPTS

Row / No.	1	2	3	4	5
1	C4	C4	C4	C4	C4
2	B17	B17	E2	E2	E2
3	E2	E2	M3	M4	M5
4	M5	M4	G3	G3	G3
5	G3	G3	C4	C4	C4
6	C4	C4	M5	M5	M5
7	M5	M5	E2	E2	E2
8	E2	E2	P2	P2	P2
9	P2	P2			
MOD	44	43	25	26	27
Time (s)	5.676	5.547	3.225	3.354	3.483

5.3. Energy expenditure calculation

The energy expenditure of order-pickers is also affected by various factors: complicated body conditions of order-pickers, weight of goods, equipment, working time etc. It changes with so many factors that a general optimal solution of storage location assignment is not available for diverse conditions. Although each specific case can be optimised, it does not make much sense in the practice.

Nevertheless, the statistics of the energy expenditure can be used in the mathematical models as constants, standing for diverse activities, to simply the optimisation problems and find a compromise. In order picking, the activities of order-pickers can be divided into two basic types: travelling and picking, causing quite different energy expenditures per unit time. So two statistical weights k_t and k_p are used in this paper to measure the energy expenditure of these activities with the unit MET (1 MET = 1 kcal/kg/hr). The energy expenditure is therefore calculated as follows:

$$f_{te}(\mathbf{G}) = k_t f_t(\mathbf{G}). \quad (8)$$

$$f_{pe}(\mathbf{G}) = k_p f_p(\mathbf{G}). \quad (9)$$

6. CASE STUDY

In this section, an example of the warehouse and picking orders are presented to illustrate the effectiveness of these algorithms.

6.1. Experiment plan

The single-block warehouse has 10 racks, 30 columns, and 5 rows. Each storage location is 0.5 m wide, 1 m long. The width of pick aisles and the half-width of cross aisles are set as 1m. According to the 5th assumption, the warehouse has 1500 SKUs.

Dong, Block, and Mandel (2004) presented that the energy consumption of a moderate walking and picking activity (shopping for food, putting groceries away) costs 2.8 MET and 2.3 MET respectively. The travel speed of the order-picker is set as 1.67 m/s.

In the experiment, the ABC-classes of SKUs are defined based on the Pareto principle, see Table 3. 3000 picking orders are generated according to the assumption that the discrete distribution of picking frequency approaches three connecting segments (Zhang 2016).

To show the advantages of these multi-objective evolutionary algorithms, both the full-turnover storage and the order-orientated storage assignment strategy are tested, in respect of four routing strategies.

Table 3: Setup of ABC-Classes

Class	Proportion (%)	Popularity (%)
A	10	70
B	20	20
C	70	10

6.2. Result analysis

6.2.1. Analysis of calculation time

The calculation time of four algorithms MIA, MIAS, MEA and MEAS, are shown in Figure 4 and Figure 5, in respect of four routing strategies. Obviously, there is a decreasing sequence of the routing strategies by calculation time: MB, SB, RB and RS, because the more complicated a routing strategy is, the more time it takes.

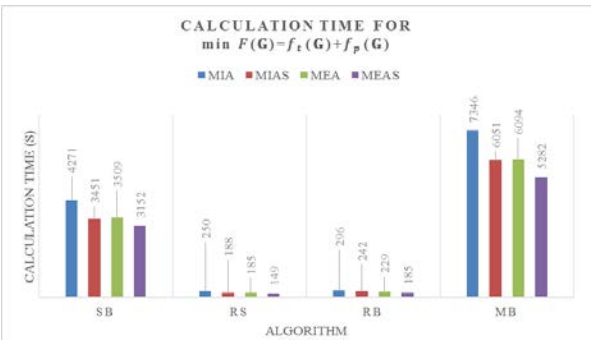

Figure 4: Calculation Time for CSF

For CSF, MIAS consumes 18% less calculation time than MIA on average, whilst the calculation time of MEAS is 12% less than that of MEA. For MF, the average reductions are 19% and 8%. Obviously, the MIAS and MEAS algorithms can improve the calculation efficiency. According to the 7th assumption, there is no change in the actual storage assignment, if the same SKUs are in the same column of the same rack. In this instance, the change of the SKU priority list is limited to a small section within a column of a rack, causing no change in the objective functions. As a result, these kinds of cases can be skipped in the optimisation.

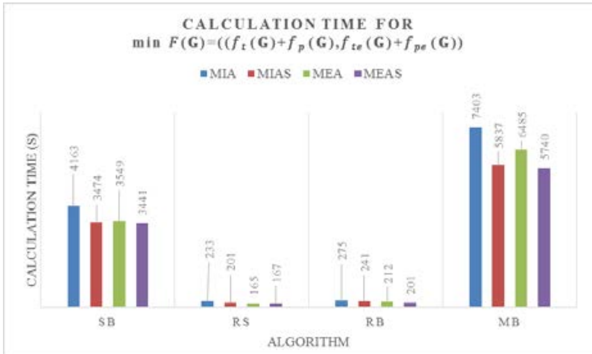

Figure 5: Calculation Time for MF

6.2.2. Improvements in order-picking

On the one hand, the time consumption of travelling and picking is calculated as an index for the converted single-objective optimisation. Figure 6 shows the reduction in time consumption by the four algorithms under diverse routing strategies, compared with the full-turnover storage. In general, MEA and MEAS always perform better than MIA and MIAS. That means the exchange method is better than the insertion method for this optimisation problem.

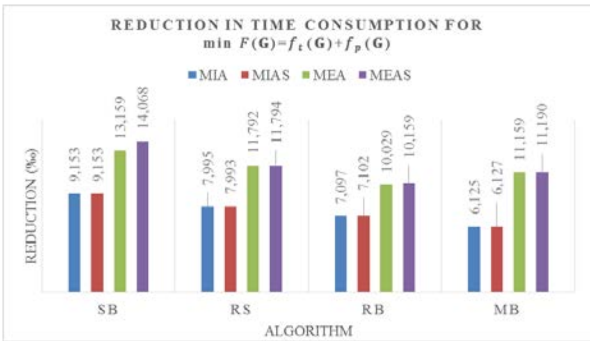

Figure 6: Reduction in Time Consumption for CSF

MEAS in particular can always lead to more reduction in time consumption than MEA. Meanwhile, the improvement of MIAS is not very stable, compared with MIA. On average, the time consumption of MEA is 3.94‰ more than that of MIA, whilst MEAS consumes 4.21‰ less of time consumption than MIAS.

On the other hand, both time consumption and energy expenditure of the picker are considered in the multi-objective optimization problem. In this case, the two indexes converge simultaneously. Figure 7 describes the reduction of time consumption, whilst Figure 8 shows the energy expenditure. Generally, MEA and MEAS perform better than MIA and MIAS at all times.

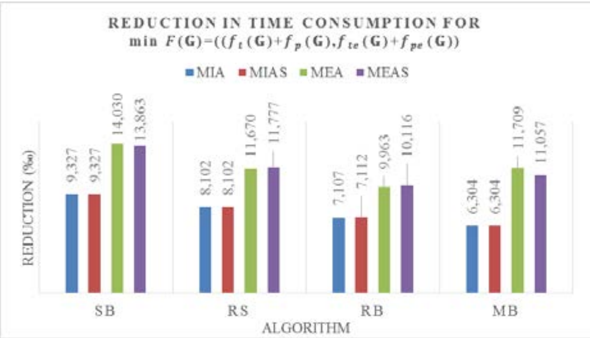

Figure 7: Reduction in Time Consumption for MF

However, MEAS does not always lead to the best improvement. The improvement of MEAS is more than that of MEA under routing strategies RS and RB. Nevertheless, there are negative results of MEAS under routing strategies SB and MB. Statistically, MEA leads to 4.13‰ and 4.18‰ reduction of time consumption and energy expenditure more than MIA. Meantime, MEAS shows 3.99‰ and 4.04‰ more improvement than MIAS.

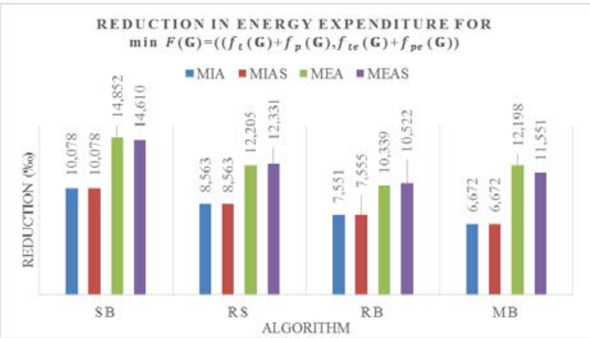

Figure 8: Reduction in Energy Expenditure for MF

7. CONCLUSION

This paper presents the four multi-objective evolutionary algorithms of a correlated storage assignment strategy, to improve the storage location assignment in picker-to-parts order-picking systems under four routing strategies. For the reduction in travel distance and pick time, the multi-objective optimisation problem is converted into a single-objective optimisation. The time consumption and the energy expenditure are further studied in the multi-objective optimisation problem with parallel convergence. In this study, the change of storage locations for single SKUs is considered to develop the algorithms, and the case study shows the advantages of these algorithms in the correlated storage assignment strategy, by comparing with the full-turnover strategy.

However, there is still great potential in the mining of picking orders and the development of effective algorithms for the multi-objective optimisation problems of warehouse management. Firstly, the correlated SKUs may be grouped into itemsets; secondly, the energy expenditure of order-pickers could be more detailed; finally, more objectives can then be set in the optimisation. Furthermore, with the application of picking robots, the energy expenditure can be quantified by power consumption. Thus, the multi-objective evolutionary algorithms should be further developed for these problems.

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