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Research on the Work-rest Scheduling in the Manual Order Picking Systems to Consider Human Factors

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Abstract. As the status of order picking in the warehousing and distribution system has been raised, the work-rest scheduling of picking becomes particularly important. Although science and technology have developed rapidly, manual picking is still essential and indispensable. However, previous researches focused on the study of the sequencing, ignoring human factors. The paper presents a work-rest schedule model in parts to picker picking system. Two objectives are proposed that include minimizing the picking time and minimizing picking error rate. And workers' fatigue, workload is taken into account in the manual order picking systems because the fatigue can have a large influence on the picking time and the picking error rate. A genetic algorithm is used to solve a multi-objective optimization problem that the model concerns and looking for a Pareto front as the most effective methods for solving this problem. Once the original data is given, the work-rest scheduling model is built and the work sequence, and the number of breaks are determined to be chosen by decision makers. In addition, a case study of the model is used to confirm that the model is effective and it is necessary to consider the human factor in the picking system.

Keywords: Work-rest schedule, picking system, fatigue, workload, picking error rate

1. Introduction

As the rapid development of the internet or the web, it has been a powerful marketing tool to introduce the concept of "electronic business" or "electronic commerce" to market transactions. As a dynamic medium, internet has channeled transactions between customers and firms in a virtual marketplace. The growth of it has been phenomenal, and there has been corresponding growth in e-commerce on this robust platform. Thus, a new marketing channel has been created by the internet and e-commerce. It is that how firms conduct so much business about e-commerce and provide logistical support activities (Cho et al. 2008).

Consumers can get products what they want by several options of driving to a traditional retail or shopping on-line. Compared with the traditional retail, e-commerce retail system requires several new approaches (Weber et al. 2009, Napolitano 2012). Of these methods, the changing of the logistical is the most obvious. Small order size, increased daily order volumes, small parcel shipments and good quality are common. It is a complicated task to get goods delivered to a customer's doorstep in a timely manner. To satisfy customers and earn their loyalty, we should take into account the efficiency and quick of the logistical distribution (Masmoudi et al. 2013, Cagliano et al. 2017). Moreover, the success of firms in the e-commerce market also depends on their distribution networks.

In the e-commerce logistics, the key is the warehouse order picking system, where loads of drastically different weights must be handled. The e-commerce firm will ultimately fail if there is not a complete order picking system. Order picking has long been identified as the most labor-intensive and costly activity for every warehouse (Goetschalckx and Ashayeri 1989, Drury 1988, Tompkins et al.

2003). The cost of the order picking system is as much as 60% of the total procedures expense (Wang and Wang 2008, Richards 2014). Any loss in order picking will lead to unsatisfactory service and high operational cost for warehouse, and consequently for the whole supply chain. In order to make the logistic efficiently, De Koster et al. (2007) considered the order-picking process should be robustly designed and optimally controlled and showed the order batching is an NP-hard problem. Thus, many companies such as Amazon, Jingdong, Dang Dang and so on, choose abandoning the traditional logistics distribution systems and built their own distribution centers to lower the cost and improve the picking efficiency.

In the warehouse order picking, although a lot of equipment options are available to apply in the picking process, including automatic storage, retrieval systems, automated convey, sortation, forklifts and automatic picking machines, the most common method within these centers is static shelving (Piasecki 2013). It means that it is not easy to use such equipment to move the goods to the static shelving. Therefore, upon most occasions, order picking is related to a labor intensive operation. Therefore, there is ample opportunity for errors in both accuracy and completeness.

To some extent, order picking behavior is a process of the manual material handling. It requires manual manipulation, such as pushing, pulling, lifting and carrying which can easily suffer fatigue (Choi 2006, Lavender et al. 2012, Grosse et al. 2015). Fatigue is the key to decrease performance. A fatigued worker's ability to perform his task may be lost or impaired. Workers who get fatigued may have decreased task speed, increase in memory errors, incorrect action and so on (Hancock and Desmond 2001, Grosse et al. 2017). Therefore, considering human factors into the order picking system is necessary.

The goal of the paper is to reasonably design and analyze manual sorting operation on the premise with fully considering human factors. The purpose of this paper is to fully consider human factors and reasonably design and analysis the manual sorting operation. This paper is organized as follows. Section 2 reviews the related literature. Section 3 presented our model. Section 4 presents the multi-objective optimization and algorithm. A case study is presented to verify the method of the paper in section 5. We give the conclusions in section 6.

2. Literature Review

2.1 Scheduling Problems with Varying Processing Time

In the last four decades, researchers have primarily concentrated on the modeling and algorithm designing of scheduling problems (Ozturkoglu and Bulfin 2012, Afzalirad and Shafipour 2018, Pei et al. 2016, Lim and Kwok 2016). Most of the previous studies assume that the processing time of the jobs are constant. However, in reality, the processing time of jobs may change, given the impacts of different factors such as deterioration and wear phenomena. Gupta and Gupta (1988) first introduced the concept of scheduling deteriorating. They introduced that the processing time as a polynomial function of its initial time. Cai et al. (1998) developed a polynomial time approximation scheme to minimize order picking makespan. Bachman et al. (2002) considered a machine scheduling problem that minimizing the maximum lateness under linear deterioration. They presented different heuristic algorithms and proved that the corresponding problem is NP-hard. Bachman and Janiak (2000) showed that the corresponding single machine scheduling problem to minimize the total weighted completion time is also NP-hard. Chen et al. (2002) proved that most of the scheduling problems are NP-hard problems. Gademann and Vande (2005) studied

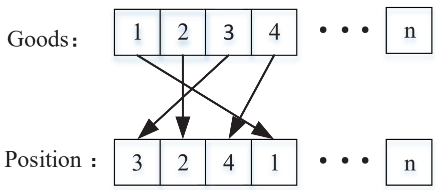

Figure 1 Schematic of Picking Model

the order picking problem by minimizing the total walking time in the picking model of arrival and proved that the problem is NP problem, and got the approximate optimal solution with iterative descent algorithm.

The picking model is shown as follows in Figure 1.

There are n goods placed in n positions. In figure 1, the good 1 is in position 4 and the good 3 is in position 1. If the picking order is [2, 3, 1, 4], then the first picked goods is in the position 2, and the position 4 is picked at last. It means that the good picking sequence is 2, 4, 3, 1.

2.2 Scheduling Problems with Human Factors

The scheduling problems mentioned above only focus on optimizing different criterion related to the performance of machine, and didn't take the human characteristics into account. In practice, in order to make the system in operation work smoothly, the work task, environment and tools over human capabilities should keep balance. Even though the advances in technology, such as in automation and the wide spread use of equipment, have done much to address and ensure the system balance, human factors continue to be significant. Therefore, the scheduling problems with human factors are important.

In recent years, most researchers have started to give more attention to scheduling problems with different characteristics including the practical issue and the person concerned, such as learning effect, aging effect, deteriorating jobs and so on. And then the most commonly studied performance measure involve makespan, total completion time, total weighted completion time, maximum lateness, maximum tardiness and number of tardy jobs (Ozturkoglu and Bulfin 2011).

Physically demanding work may not only lead to physical fatigue but also lead to negative problems such as inefficient productivity, poor quality work, reduced job satisfaction and possible disorders (Nechaev 2001, Sheikhalishahi et al. 2016, Smith and Gallagher 2018). Thus, proper organization of work can be avoiding physical fatigue in workers. Rudin-Brown et al. (2018) reported that job rotation can decrease both perceived load and energetic load among the employees of a refuse collecting department. Tharmmaphornphilas et al. (2003) presented a mathematical model to create job rotation schedules to minimize the noise exposure for laborers working in sawmill. In addition, Hsie et al. (2009) proposed a work-rest scheduling model with minimizing workers' extra energy expenditure. In his study, physiological factors were considered, but the duration of each break was identical and it was not convenience to be controlled. In Ozturkoglu and Bulfin (2012) study, the work sequence, the place of each break, and the number of breaks with considering the physiological factors in their model are determined. They also motivated by manual order picking activities in warehousing systems. However, the objective functions are both time-related and it is not sufficient to evaluate the whole order picking system.

2.3 A Classification of Order Picking System

The order picking system can be distinguished into two forms, namely manual order picking systems which can be operated by human factors, and technical systems, in which the process of retrieving articles from the warehouse is completely automated. In the first group, two kinds of manual order picking systems can be further differentiated in practice. They are parts-to-picker systems and picker-to-parts systems.

In parts-to-picker systems, one or several pickers are located and the unit loads from the warehouse are retrieved by automated storage and retrieval systems. In this ground, the order pickers choose which items are requested and then remove them in a specified order. And the automated storage and retrieval systems returns the unit load to its location in the warehouse. In picker-to-parts systems, the pickers are moving. They need to walk or ride through the picking area, stop at the storage locations of the articles, and removes the required units or items. In different kinds of picker-to-parts systems, the units can be moved from pallets, bins or the warehouse floor. Moreover, the picking area also consists of high storage racks, a vehicle, a crane and so on (Henn et al. 2012, Napolitano 2012).

To some extent, the parts-to-picker system is similar to the picker-to-parts systems but not considering the workers' walking distance. Therefore, we will concentrate on the type of the parts-to-picker systems in this paper to validate that considering human factors is quite necessary.

In this study, we focus on the order picking system in the e-commerce logistic field. Then, on the base of the analysis of the scheduling, the work-rest model can be acquired with taking account into human factor, such as workload, fatigue, while determining the picking items sequence, the number of breaks, and the optimal break schedule. For multi-objective programming, there are often conflicts between objective functions, and there is almost no single optimal solution, that is, absolute optimal solution can't be obtained. Therefore, only according to the characteristics of the problem, appropriate algorithm can be used to obtain its satisfactory solution, that is, Pareto solution. Our model is based on one developed by Ozturkoglu and Bulfin (2012). This paper differs from previous studies:

(1) Seeing the operation of picking items in the e-commerce logistical distribution as a scheduling problem.

(2) Considering the picking time is not a constant, but can be changed by the fatigue.

(3) Considering the operation of picking items more comprehensive, not only minimizing makespan past studies have involved, but increase to the error rate of the whole process. And finally, a series of Pareto solutions are given in order to select.

3. The Mathematical Model

Manual order picking is the most important part in the warehouse distribution order picking. It is also the fulfillment of outbound customer order requests by way of manually retrieving articles stored within warehouses and all kinds of the requirements of the distribution centers at the same time. Because of the diversity of the good requests and the nature of the operation, many units can vary considerably in terms of characteristics, such as their shape, size, and weight. Also it can be classified by their storage location, and retrieval requirements, thereby dictating the order picking method such as single piece, case, or pallet picking (Watts 2010). To some extent, it increases the difficulty and the rate of error in the order picking. The workload is one of the most important factors which have influence on the error rate. According to the difference of the energy expenditure when ones are working, we can divide workload into three types, low-level workload, middle-level workload and high-level workload. In low-level and middle-level workload, order pickers can work for 8 hours continuously without feeling fatigue. They can work a long time with a good health (Li 2008). Thus, in this situation, when order pickers looking for the requested goods and remove them, the error rate will stay in the low. In contrast, when order pickers work in the high-level workload, the frequencies of the human errors will rise lately. As a result, the accurate rates of the order picking reduce obviously. In a word, when workload is higher, human error is more difficult to decrease. And then, the error of the order picking is more available (Zhao et al. 2015, Hanson et al. 2016).

There are two methods applied to distribute the workload on the basis of energy when a worker is working so far. One is the relative index, such as the relative metabolic rate. The other method is named absolute index, such as energy expenditure (Li 2008). In this paper, we combine these two methods into one integrated model to distinguish the workload.

3.1 Model Premise

According to accumulating the relative index, the energy expenditure Q can be acquired. Then we can get the threshold value of the energy expenditure $\overline{Q}$ by determining the maximum acceptable work duration which can be got by measuring heart rate (Wu and Wang 2001). Moreover, comparing Q and $\overline{Q}$, the error rate can be acquired easily. Finally, heat consumption can be used to measure ones' energy expenditure and the threshold value of the energy expenditure. In this method, only heart rate, height and weight will be available.

$$Q = (RMR + 1.2) \times (BNR \times BSA \div 60) \times T \quad (1)$$

$$\overline{Q} = MAWD \times \overline{E} \quad (2)$$

$$BSA = 0.0061 \times B + 0.0128 \times M - 0.1529 \quad (3)$$

$$RMR_{\text{male}} = 0.072 \times HR - 5.608 \quad (4)$$

$$RMR_{\text{female}} = 0.065 \times HR - 4.932 \quad (5)$$

$$BMR_{\text{male}} = (13.7 \times M + 5.0 \times B - 6.8 \times Age + 66) \div (24 \times BSA) \quad (6)$$

$$BMR_{\text{female}} = (9.6 \times M + 1.8 \times B - 4.7 \times Age + 655) \div (24 \times BSA) \quad (7)$$

$$MAWD = -2.67 + e^{7.02 - 5.72 \times RHR} \quad (8)$$

$$RHR = (HR_{\text{work}} - HR_{\text{rest}}) \div (HR_{\max} - HR_{\text{rest}}) \times 100\% \quad (9)$$

Where RMR is relative metabolic rate, BMR is basic metabolic rate, M, B, BSA, Age is the body mass, height, surface area and age respectively, HR is picking heart rate, T is picking time, $\overline{E}$ is the threshold value of the energy expenditure in one minute. It equals to 41.9 kJ/min (10.056 kcal/min) (Shi et al. 2011), $MAWD$ is maximum acceptance work duration, RHR is relative heart rate, the value is related with working heart rate (HR_{work}), resting heart rate (HR_{rest}) and maximum heart rate ($HR_{\max}$).

3.2 Model Assumptions

- Breaks should be taken during work shifts.
- Order picking but not batch picking.
- Only considering the scheduling in the same order.
- There is no priority in any order.
- One person, one good at the same time.
- Goods are stored randomly in the static shelves.
- Order pickers will have a rest when they get to the next shelves.
- The heart rate is constant when pickers are working.
- The pickers can recover completely after breaks.
- In different workload, the probability of error rate of order picking is different.

3.3 Model Parameters

n is the number of goods to be picked.

i indicates the position number, which is from 1 to n.

k_j indicates the last rest position number until workers pick in the i th position, which is from 0 to n-1.

$$k_i = k_{i-1}\left(1 - y_i\right) + i y_i \quad (10)$$

j indicates the goods number, which is from 1 to n.

q is the fixed processing time to have a rest.

p_j is the initial processing time of picking good j.

$p_{j(i-k_i+1)}$ is the processing time of picking good j if picked in $(i-k_i+1)$th position after having a rest, in other words.

$$p_{j(i-k_i+1)} = (1+\alpha)^{i-k_i} p_j \tag{11}$$

α is the fatigue factor for $0 \leq \alpha \leq 1$ delayed by one position, λ_1 is the error rate in low and middle workload, λ_2 is the error rate in high workload, Q_{ij} is the energy expenditure when picking good j in ith position, $\overline{Q_j}$ is the threshold value of the energy expenditure when picking good j, D_i is the ratio between the energy expenditure and the threshold value of the energy expenditure in the ith position, S_i is the error rate in ith position, C_i is the makespan in ith position.

3.4 Decision Variables

x_{ij}=1 if good j is picked in ith position, otherwise zero.

y_i=1 if having a rest before picking in ith position, otherwise zero.

3.5 Objective Functions

$$Minimize \quad Z_1 = \max_i \{C_i\} \tag{12}$$

$$Minimize \quad Z_2 = 1 - \prod_{i=1}^{n} (1 - S_i) \tag{13}$$

To solve this problem, the objective of minimizing makespan and error rate is used.

3.6 Mathematical Model

$$C_1 = \sum_{j=1}^{n} p_{j1} x_{1j} \left(p_{j1} = p_j\right) \tag{14}$$

$$C_i = C_{i-1} + \sum_{j=1}^{n} p_{j(i-k_i+1)} x_{ij} + q y_i \tag{15}$$

$$\sum_{i=1}^{n} x_{ij} = 1 \quad j = 1, \ldots, n \tag{16}$$

$$\sum_{j=1}^{n} x_{ij} = 1 \quad i = 1, \ldots, n \tag{17}$$

$$Q_{ji} = \left(RMR_j + 1.2\right)\left(BMR \times BSA/60\right) p_{j(i-k_i+1)} \tag{18}$$

$$\overline{Q}_j = MAWD_j \times \overline{E} \tag{19}$$

$$D_i = Q_{ji}/\overline{Q_j} \tag{20}$$

$$S_i = \lambda_1 (1 - I(D_i)) + \lambda_2 I(D_i) \left(\text{which} \quad I(x) = \begin{cases} 1, \text{when} & x \geqslant 1 \\ 0, \text{when} & x < 1 \end{cases}\right) \tag{21}$$

$$0 \leqslant \lambda_1 < \lambda_2 \leqslant 1 \tag{22}$$

$$x_{ij} \leqslant y_{i+1} \quad i, j = 1, \ldots, n \tag{23}$$

$$x_{ij} \in \{0, 1\} \quad i, j = 1, \ldots, n \tag{24}$$

$$y_i \in \{0, 1\} \quad i = 1, \ldots, n \tag{25}$$

$$C_i \geqslant 0 \quad i = 1, \ldots, n \tag{26}$$

In constraint (14), the completion time of picking in position one is equal to the processing time of picking good assigned to position one. In constraint(15), the completion time of picking in position i is equal to the completion time of picking in position i-1 plus the processing time of picking good assigned to position i, and plus the walking time. In constraint (16), each goods can be picked by one person. In constraint (17), each worker can pick one goods. In constraint (18), the energy expenditure when workers pick good j in position i is determines. In constraint (19), the threshold value of the energy expenditure when picking good j is ensured. In constraint (20), D_i is equal to the energy expenditure and the threshold value of the energy expenditure in position i. In constraint (21), the error rate in position i is proposed. In constraint (22), it presents the level of error rate is always within prescribed acceptable limits. In constraint (23) the relationship between the decision variables is proposed. Last, in constraints (24), (25), and (26), it

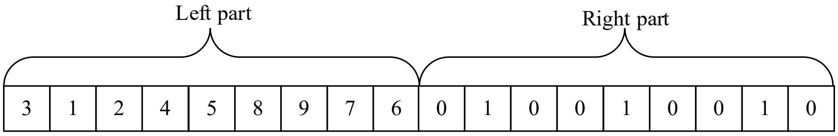

Figure 2 Schematic of Individual

indicates that the decision variables are binary and all other variables are non-negative.

4. Multi-objective Optimization and Algorithm

In this study, the goal for the work-rest schedule creation is to acquire the goods that are picked in warehouse schedule that minimizes both the duration for picking goods and the error rate. Thus, the model can solve the multi-objective optimization problem.

Multi-objective optimization involves the problem of seeking solutions over a set of possible choices to optimize more than one criterion. Various approaches, such as multi-objective weighting and a utility function, can reduce this problem to a scalar optimization problem. Various solutions may exist in the same multi-objective optimization problem. In addition to the complexity of this model that refers to two objective functions, the problem in this paper presents several difficulties.

Genetic algorithms are widely used to solve multi-objective problems (Lins and Droguett 2011, Nastasi et al. 2016, Sana et al. 2018). Genetic algorithm is a type of search algorithm developed by Holland. It is on the basis of the natural selection and genetics. And also it is used to search through a decision space for optimal solutions. Thus, a series of Pareto fronts, as in this paper, are proposed. A Pareto front means that in the model, no objective function can be improved without sacrificing at least one of the other objective functions (Gen and Cheng 2000, Kim and Weck 2005, Ishibuchi et al. 2017). It is several types of Pareto optimal solutions in the multi-objective case and cannot be simply compared with each other.

In this algorithm, decisions or a potential solution to a problem are represented by a string. Fitness function is used to evaluate each string's performance. The ones that having the better performance is more likely to survive than others. The most important part in GA is the exchanging and perturbing of the genetic information. This happens between strings by crossover and by mutation. The process is repeated until the strings in the new generation are identical or the termination conditions are satisfied (Cheng and Chen 2007, Marichelvam et al. 2014).

In this scheduling model, when workers have a rest, the processing time will be delayed. But when the behavior of pickers having a rest, have a better performance than the rising of error rate and the increasing of the time of a single picking job, we will assign pickers to have a good rest, otherwise to pick all the time.

The steps for this work-rest schedule model are described as follows.

Step1: Initialization. An individual which stands for a solution contains two parts as follows in Figure 2.

Each part contains N genetic positions. The left part guides for the picking order and the right guides for whether worker have a rest or not. In the left part, the goods 3 will be first picked and the goods 6 will be picked finally. In the right part, 0 stands for not rest and 1 stands for rest. So before the second, the fifth and the eighth picking there is a rest for worker. T individuals compose into a chromosome.

Step2: Calculate object values. Each solution corresponds a set of object values. Two object values here, one is the picking make span and the other is the error rate.

Individual 1:	3	1	2	4	5	8	9	7	6	0	1	0	0	1	0	0	1	0
Individual 2:	1	3	2	4	8	9	6	7	5	1	1	0	1	1	0	0	1	1
	Crossover																	
New individual 1:	3	1	2	4	5	9	6	7	5	1	1	0	1	1	0	0	1	1
New individual 2:	1	3	2	4	8	8	9	7	6	0	1	0	0	1	0	0	1	0

Figure 3 Crossover Operation

Table 1 Detailed Information of Workers

Height (cm)	Weight (kg)	Age	Gender	HR_{rest} (beat $\cdot$ min^{-1})	HR_{max} (beat $\cdot$ min^{-1})
170	75	35	male	70	190

Step3: Optimum checking. Once there is an optimum solution, then the individual which corresponds with the optimum solution will be cloned some times. These individuals will compose into best chromosomes.

Step4: Pareto solutions. If there is no optimum Pareto solutions will compose into best chromosomes.

Step5: Generate new chromosomes. Before generating new chromosomes, the number of individuals in best chromosomes should be counted. Assume the number is M, which means that $T-M$ individuals should be generated. The new generated is called offspring and the parent is the best chromosomes in step3 or step4. Best chromosomes will be selected, crossed and even mutated, finally the $T-M$ offspring are generated.

The crossover and the mutation operations are as follows in Figure 3.

There is a mistake in the new individual 1 according to Figure 3. The number '5' with underline should be corrected into '8' because the goods 8 has not been picked and the goods 5 has been picked twice. The mutation position is limited exactly, the position $P \in [N+1, 2N]$. If the number in the position is 1 then it will be changed into 0; when the number is 0 then it will be changed into 1. Both $T-M$ new generated and the M best individuals compose into new chromosomes which contains T individuals.

Step6: Stopping criterion. When the loop has run 200 times, the loop is end.

5. Case Study

A computational experiment is conducted to test the performance of the mathematical model. This example involves 9 items that are picked by one worker. Table 1 summarizes the information of the picker, including gender, age, height, body mass, heart rate and so on. Table 2 provides each item's picking time, maximum picking time, heart rate when it is picked. An appropriate selection of values of parameters would improve the effectiveness while searching optimal solutions in GA. Therefore, in this case study, we have several other assumption, for example, the rest time is 15 minutes, in low-level workload and high-level workload , the error rate are 0.3% and 2.3% respectively, and the fatigue rate α is assumed to 0.03 (Ozturkoglu and Bulfin 2012), In the study, they had analyzed the average run time for make span in different α.

To verify the validity of considering the human factors, a contrast plan which is widely adopted in many picking systems is set as follows:

1. Picking orders according to the initial sequence.

2. After picking three items there is a fixed

Table 2 Detailed Information of the Picked Goods

Number	Picking time(min)	Maximum picking time(min)	HR(beat · min^{-1})
1	20.5	82	155
2	27	72	90
3	10	22	120
4	3.1	60	180
5	11	110	110
6	12	19	135
7	8.2	130	168
8	8	150	145
9	7.2	10	170

Table 3 The Value of the Objective Functions in the Feasibility Solutions

Number	Makespan (min^{-1})	Error rate(%)
1	151.222	6.16940407
2	121.222	17.64219469
3	141.222	7.02040407
4	161.222	3.952187328
5	161.6749	7.83260407

rest time.

A random case is shown as follows:

Table 1 and Table 2 show the detailed information of the workers and the picked goods.

On the basis of the above mentioned information and GA algorithm, there are five solutions obtained and shown in Table 3.

The number 5 solution is a contrast. In the last solution, the picking order is 1 2 3 4 5 6 7 8 9, and picking worker have a fixed rest after picking two goods. In the first four solutions, there is no best choice. In other words, one solution with lower makes span must have a higher error rate. The first solution performs better than the second according to the index of error rate, but have a longer makespan than the second. The result is shown in Figure 4.

As shown in Figure 4, the fifth solution is a bad choice. It has a worse performance not only in make span but also in error rate compared with the second and the third solution. In other words, only the picking order has been calculated, the picking performance can be improved. Next, the original and detailed information of the picking is presented as follows in Table 4.

Table 4 shows assignments under many different solutions. For the first solution, the third goods will be picked firstly and the second goods will be picked after other goods. And before picking the sixth, eighth and the first goods, there is a rest for workers to relax. If they keep working, the performance is getting worse. And the contrast solution is a proof to verify the necessity of the calculation.

6. Conclusions

Order pickers usually perform jobs in the warehouse distribution where loads of drastically different weights must be handled in a stochastic pattern. It means that their works are highly physically demanding. This physically demanding works not only lead to physical fatigue but lead to a loss in accurate rate of order picking. As a result, there is a need for systematic way of arranging worker's picking job

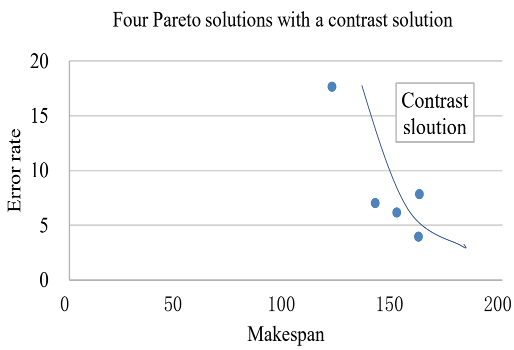

Figure 4 Four Pareto Solutions with a Contrast Solution

Table 4 The Detailed Information of the Picking Order Corresponding to Table 3

Number	Picking order									Rest or not								
1	3	6	9	8	7	5	1	4	2	0	1	0	1	0	0	1	0	0
2	5	9	1	6	2	7	3	4	8	0	0	0	0	0	0	0	0	0
3	6	5	2	9	1	4	8	3	7	0	0	0	1	0	0	0	0	1
4	4	5	2	3	7	1	8	6	9	0	1	1	1	0	1	0	0	0
5	1	2	3	4	5	6	7	8	9	0	0	1	0	0	1	0	0	1

that allows pickers sufficient breaks but does not stay with the high error rate.

In the paper we studied the picking system of the self-built logistics distribution center under the B2C e-commerce mode. Considering the human factors and multi-objective constraint, a work-rest schedule model is built with minimizing the picking time and minimizing picking error rate in picker-to-parts picking system. In this approach, a GA-based mechanism and a scheduling model for creating a work-rest schedule that balances the minimization of both the make span for order picking and the error rate during picking items due to inappropriate work arrangements. There are a series of Pareto solutions to select since these assignment plans provide a low level error rate or a short picking time than other plans. And it is clearly that when fatigue is taken into account the scheduling plan is changed a lot. In addition, according to the case study, we revealed that the proposed model about manual order picking could be efficient and necessary to consider the human factor in the picking system. In other words, it is quite important to considering the human factors into manual order picking to improve the manual picking system. Usually, it does not make the picking time longer but reduce picking time as well as lower picking error rate.

However, to practically apply and promote this scheduling mechanism, such model should be further improved in several groups. Firstly, this article deals with the scheduling problem on the basis of picker's constant heart rate. But to reflect real industrial applications, in the further research, we should assume that the heart rate is dynamic. Moreover, in this model, the worker recovers completely after having a rest. But in practice, people cannot have a total recovery even though he has a good rest. Besides, the walk distance should be considered. Therefore, it is worth to have an intensive research in the future.

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