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WAREHOUSE STORAGE ASSIGNMENT FOR SURFACE MOUNT COMPONENTS USING AN IMPROVED GENETIC ALGORITHM

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ABSTRACT

The assembly process of surface-mount device (SMD) usually requires over hundreds of types of surface-mount components (SMC). A set of SMCs should be picked in the warehouse to be supplied to the production line. We define a storage location assignment problem for SMC considering a periodic production plan to improve the efficiency of the SMC-picking operation. We propose a solution approach based on Genetic Algorithm (GA) to solve a reduced problem that finds the optimal allocation sequence of each type of SMC. We generate the initial population based on the characteristics of the SMCs, such as the production plan and the bill of material (BOM). A simulation model based on AutoMod is used to compare the performances of the proposed algorithm and some practical legacy methods with the empirical data. The simulation results demonstrate that the proposed algorithm is feasible and efficient in terms of picking distance.

1 INTRODUCTION

The manufacturing process of surface mount device (SMD) mainly involves an assembly of hundreds of types of electronic components onto a printed circuit board (PCB). A set of different types of electronic components, which we call surface-mount components (SMCs), should be kitted at the warehouse to be supplied to each production line. For kitting the SMCs, workers or retrieval robots are to move to several storage locations to pick the required SMCs. The picking operation is usually time-consuming since thousands of types of SMCs are stored in the warehouse and each SMD model requires hundreds of different combinations of SMCs, according to its bill of material (BOM). Depending on the storage location of SMCs, the picking distance or travel time could vary for each model. In practice, the storage location of SMCs is determined based on its characteristics, such as material similarity, weights, or supply frequency. This paper aims at reducing picking distance with a practical storage location assignment method, considering the characteristics of SMCs.

There have been a number of studies on warehouse storage assignment (Rouwenhorst et al. 2000; De Koster et al. 2007; Roodbergen and Vis 2009; van Gils et al. 2018; Ansari and Jeffrey 2020). Rouwenhorst et al. (2000) classified the types of warehouses into production and distribution warehouses. They discussed the warehouse design problems at three different levels: strategic, tactical, and operational levels, where the storage location assignment problem is classified as the operational level design problem. De Koster et al. (2007) investigated a number of practical warehouse storage assignment methods, such as random storage, closest open location storage, frequency-based storage, class-based storage, and family grouping. For the random storage rule, an item's storage location is randomly assigned with an equal probability for all locations. The closest open location storage is to allocate an item to the closest or the first empty location. Frequency-based storage or full-turnover-based storage determines the storage location based on the item's demand frequency, and more frequently requested item is located near the In/Out (I/O) points. Class-based storage, also referred to as ABC storage, is to classify items into three classes (A, B, or C) based on their request frequency and random storage is applied within the same class. Family grouping considers the relation between items and place the similar items close to each other. Roodbergen and Vis (2009) provided a survey on warehouse design and operational decision problems with a focus on automated storage and retrieval system (AS/RS). They discussed the studies on validating the performance of storage assignment rules with simulation and analytical analysis. Ansari and Jeffrey (2020) adopted a clustering method to improve the performance of multi-picking warehouses. They found that the number of clusters is highly correlated to the performance of picking operations. In this paper, we define a storage location assignment problem for the production warehouse that stores the SMCs for SMD assembly. Our proposed storage assignment method considers the unique characteristics of SMC picking where over a hundred of different parts are picked together to be supplied to the production line. We reflect the advantages of both class-based and family grouping storage method by using the relevant data such as a production plan and a BOM. The performance of the proposed algorithm is validated by comparison with existing rules using simulation.

Genetic algorithm (GA) has been widely used to improve the operational efficiency in production and distribution environment since it was suggested by Holland (1992). Because the storage assignment problem is considered to be NP-hard, there have been a number of studies that propose GA-based heuristic algorithms. Bazzazi et al. (2009) applied a genetic algorithm to a storage space allocation problem in a container terminal to minimize the storage/retrieval times of containers. Bottani et al. (2012) explored a GA on allocating new item to improve the order picking operation in a class-based storage system. Ene and Öztürk (2012) suggested a GA-based storage location assignment, batching, and routing method focusing on the application to automotive industry. Pan et al. (2015) developed a genetic based heuristic method to solve storage assignment problem by considering picking line imbalance and replenishment of products. Li et al. (2016) investigated a dynamic storage assignment problem with a greedy GA considering a mutual affinity between products and an ABC storage. Guan and Li (2018) proposed a GA for scattered storage assignment problem in Kiva mobile fulfillment system, where pods are carried by automated guided vehicle to workstations.

There have been few studies on storage location assignment that have considered the production plan and the BOM. Xiao and Zheng (2010) developed a multi-stage heuristic for storage location assignment problem considering BOM information and production rates. However, the objective of their study was to minimize the number of visits to separated zones, whereas our study seeks to minimize total travel distance. The contribution of the paper is that we introduce a practical industrial problem of warehouse storage assignment, especially considering the characteristics of SMD manufacturing. Another contribution is that we propose a heuristic-based genetic algorithm to solve the storage assignment problem in a timely manner. We evaluate the performance of the proposed algorithm with the real-world scenario of SMC warehouse based on the empirical data.

The remainder of the paper is structured as follows. Section 2 describes the storage location assignment problem for SMCs and a mathematical formulation for the problem. Section 3 presents a solution approach, which is based on a genetic algorithm with a heuristic procedure. In Section 4, we conduct a series of experiments to analyze the performance of the proposed algorithm. Finally, Section 5 concludes this paper.

2 PROBLEM DESCRIPTION

We consider a SMC warehouse that have multiple aisles and racks, which is based on a real-world environment (Figure 1). Each row of the rack may have multiple layers or floors. According to the production plan and the BOM information, a set of SMCs is prepared for each planned SMD model and supplied to the production line. We assume that each picker is assigned a list of the SMD models and sequentially picks a set of SMCs for each model. We do not consider situations in which the pickers aggregate the quantities of SMCs commonly used in multiple SMD models and pick those kinds of SMCs together, because it will take more time after picking to classify and kit the appropriate combination of SMCs for each production line. The storage location assignment decision is made periodically or upon arrival of new SMC inventory from the upstream.

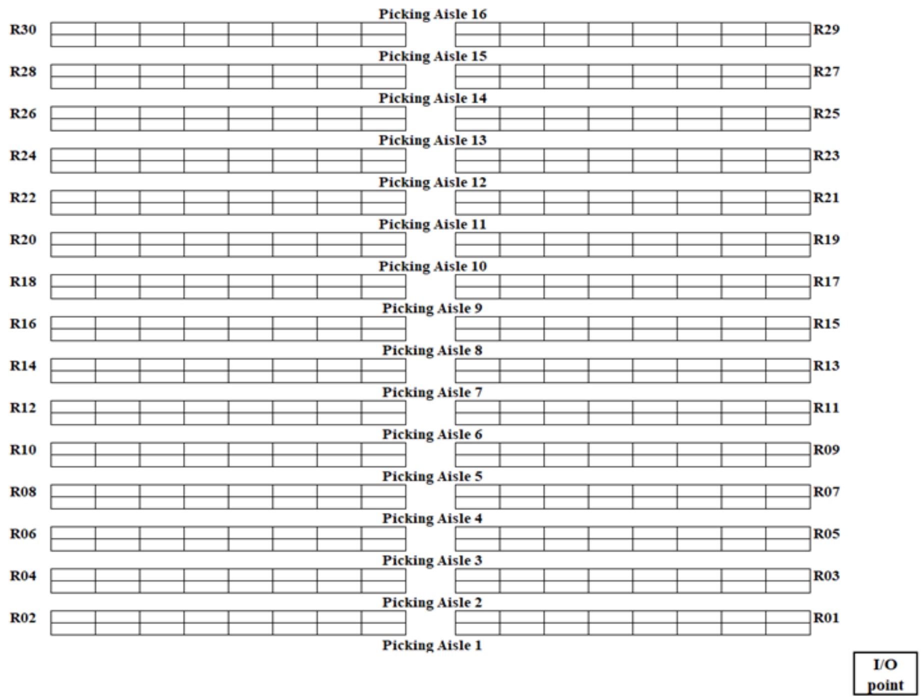

Figure 1: Illustrative example of SMC warehouse layout.

We aim to minimize the picking travel distance by optimizing storage location assignment. The actual picking distance can be affected by the visiting sequence of each storage location. Based on typical field operations, we assume that the pickers travel from the nearest aisle to the far one from the I/O point and visit appropriate aisles where the target SMCs are located. Depending on the distance from the I/O point, it is assumed that each aisle has a weight or penalty. Using this distance weight, we estimate the SMC picking distance for each SMD model as the sum of the weights of the aisles to be visited for picking, based on the storage location and the BOM information. The total picking distance is calculated by multiplying the estimated picking distance by the production frequency, where the production frequency can be specified through the production plan. The objective of our storage assignment problem is to minimize the total picking distance for a given production period. In each storage location, which is referred to as bin, only one type of SMC is assigned. Additional constraints such as capacity of racks and continuous placement of the same type of SMC are to be considered.

We define the SMC storage location assignment problem with an integer linear programming formulation. The notation and mathematical formulation are shown as follows.

Indices:

m	Index of SMD models, $m = 1, 2, \dots, M$,
c	Index of SMC types, $c = 1, 2, \dots, C$,
a	Index of aisles, $= 1, 2, \dots, A$,
b	Index of bins, $b = 1, 2, \dots, B$.

Parameters:

f_m Production frequency of model m,
q_c Storage quantity of SMC c (Unit: Bin),
w_a Distance weight of aisle a,
λ_{mc} 1 if SMC c is used for SMD model m, 0 otherwise,
θ_{ab} 1 if bin b is located at aisle a, 0 otherwise.

Decision Variables:
x_{cb} 1 if SMC c is assigned at bin b, 0 otherwise,
y_{ca} 1 if SMC c is assigned at aisle a, 0 otherwise,
z_{ma} 1 if SMD model m is assigned at aisle a, 0 otherwise,
s_{cb} 1 if the storage location of SMC c starts from bin b, 0 otherwise.

Objective:

$$minimize \ \sum_m f_m \sum_a w_a z_{ma} \tag{1}$$

Subject to:

$$\sum_b x_{cb} = q_c \ \ \forall c \tag{2}$$
$$\sum_c x_{cb} \le 1 \quad \forall b \tag{3}$$
$$\sum_b^{b+q_c-1} x_{cb} \ge q_c s_{cb} \ \ \forall c, b \tag{4}$$
$$x_{cb} - x_{c,b-1} \le s_{cb} \quad \forall c, b > 1 \tag{5}$$
$$y_{ca} \ge \theta_{ab} x_{cb} \quad \forall c, a, b \tag{6}$$
$$z_{ma} \ge \lambda_{mc} y_{ca} \quad \forall m, c, a \tag{7}$$
$$x_{cb}, y_{ca}, z_{ma}, s_{cb} \in \{0, 1\} \ \forall m, c, a, b \tag{8}$$

The objective function (1) minimizes the sum of the picking distances for the planned SMD models. The production frequency of each model (f_m) is obtained from the production plan. Constraint (2) is used to ensure that every SMC is stored in the warehouse. Depending on the inventory level of each SMC, the required number of bins could be more than one. We assume that the number of required bins for each SMC is known and the total number of bins in the warehouse is large enough to store all SMCs. Constraint (3) ensures that no more than one type of SMC is assigned to each bin. Constraint (4) and (5) let the same type of SMC to be stored sequentially in the adjacent bins. Constraint (6) defines the relationship between x_{cb} and y_{ca}. Constraint (7) is used as a bound the picking distance of each model using the BOM information. Constraint (8) represents the conditions on the decision variables.

3 SOLUTION APPROACH

The storage location assignment problem is generally considered to be NP-hard (Wang et al. 2020). Using a commercial optimization solver, we could find the optimal solution for small-size instances. However, the model is intractable for industry-size instances where the number of SMC types and the number of bins generally range from hundreds to thousands. In order to be used in the actual manufacturing sites, the assignment decision should be made within a few seconds. Therefore, we develop a heuristic algorithm to solve the problem with large-size instances in a timely manner.

GA has been employed for many years to deal with the complex optimization problems. In order to apply GA to the SMC storage assignment problem, we convert the problem of assigning SMCs to each bin into the problem of deciding the allocation sequence of each type of the SMC. Once the allocation sequence is determined, the SMCs are placed in the order close to the I/O point according to the sequence. The bins are assumed to be indexed in the order close to the I/O point. The SMCs are stored from the smallest indexed bin to the largest one in the determined order. When sequentially arranged, the number of required bins for an SMC type can be larger than the remaining bin of the rack and the same type of SMC may be stored in different racks. To prevent such as case, if the required number of bins is greater than the remaining space of current rack, those types of SMCs are placed on the next rack and the SMC in the next order is placed in the remaining space.

The overall flowchart of the proposed algorithm is shown in Figure 2.

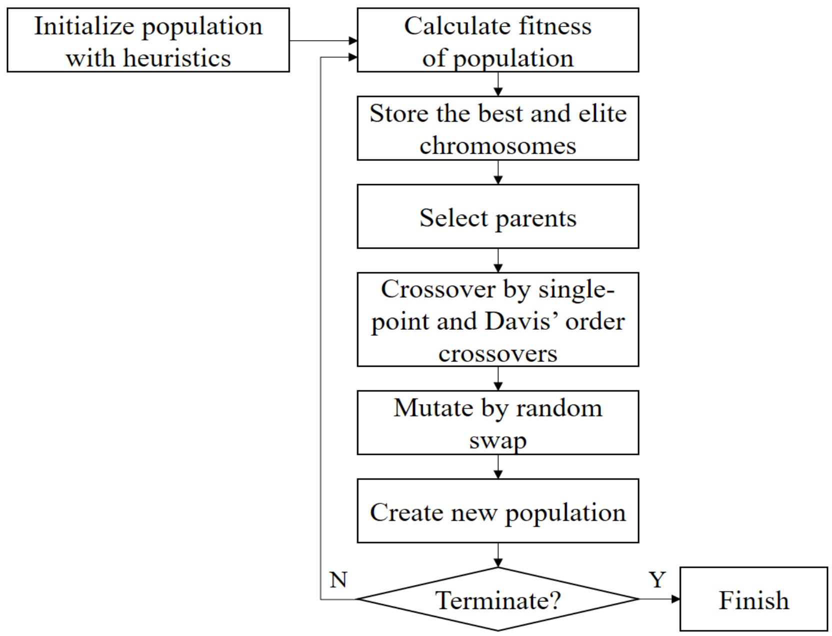

Figure 2: Flowchart of the proposed algorithm.

3.1 Chromosome Representation

The chromosome represents the allocation sequence of the SMC type. The length of the chromosome is the number of SMC types. The example of the chromosome with 10 SMC types is shown in Figure 3.

5	3	8	10	7	1	6	2	4	9

Figure 3: Example of chromosome design.

3.2 Population Initialization

The performance of GA is known to be affected by the quality of the initial population. Therefore, we generate an initial population, which is expected to be a set of good feasible solutions, based on the input data characteristics. We consider mainly three types of characteristics: production frequency of SMD models (*model frequency*), usage frequency of SMC types (*material frequency*), and storage quantity of SMD types (*material quantity*). Model frequency is calculated by the sum of the daily production frequency of each model for a given production period. Material frequency is obtained by adding the frequency of usage of each SMC using the BOM information of the planned SMD models. Material quantity is the sum of the storage quantity of each SMC. We create the following four types of heuristics that combine these characteristics to produce chromosomes expected to be superior.

- *Heuristic 1*: Sorted by material quantity
- *Heuristic 2*: Sorted by material frequency and material quantity

- *Heuristic 3*: Sorted by model frequency, material frequency, and material quantity
- *Heuristic 4*: Sorted by model frequency, material frequency, and material quantity considering the storage capacity of aisles

Heuristic 1 simply sorts the SMC types by their quantity. Heuristic 2 first sorts the SMC types by the material frequency and then by material quantity for those with the same material frequency. Heuristic 3 lists the SMC types of the SMD model with the most frequency and sorts the SMC types by the material frequency and quantity within the same model. The procedure is repeated for all models in order of frequency. Heuristic 4 is the same as Heuristic 3, except that it considers the storage capacity of aisles. The storage capacity of each aisle is calculated by the sum of the number of bins located at the aisle. As mentioned above, when placing the SMC types according to the sorted allocation sequence, the same SMC type can be separated and stored in different racks with different aisles depending on the required storage quantity and the available storage space. Those cases are not preferable in practice and therefore we swap the location of such SMC types to the location of the available SMC types in the next order. Each heuristic generates 1 chromosome, thereby resulting 4 chromosomes in the heuristic procedure. The rest of the population is generated by random permutation.

3.3 Crossover and Mutation

In order for the offspring to inherit the characteristics of superior parents, we use two types of well-known crossover methods: the single-point crossover and the order crossover by Davis (1985). By considering the nature of the sequence in which the duplicated SMC index is not allowed, we slightly modify the single-point crossover such that the left part of the designated crossover point is inherited by parents and the right part is randomly generated. For the order crossover, a segment of chromosome is inherited by one parent, and the other parts are sequentially filled with the other parent's chromosome without duplication.

To add diversity to the population and explore the search space, we mutate some of the offspring by selecting two of its genes randomly and swapping them.

3.4 Selection and Elitism

We evaluate each chromosome in the population and select some of the superior chromosomes as parents. The fitness function is the same as the objective function of the mathematical model. We first convert the solutions, which are in the form of chromosome, to the allocation results considering the capacity of the racks and the practical layout conditions such as avoiding the same SMC type being stored in different racks. We then calculate the fitness function of the allocation results. Additionally, we apply elitism strategy by preserving a set of superior chromosomes as the elite population and maintaining them in the next generation to further improve the efficiency of GA.

4 EXPERIMENTS

We conduct two types of experiments. First, we investigate whether the proposed approach with heuristic initialization has better performance than the general GA with random initialization. Second, we employ simulation experiments to validate the effectiveness of the proposed algorithm in terms of reducing picking distance. We compare the simulation results from the proposed algorithm and those from general storage assignment methods such as the frequency-based sorting policies that have been practically used in manufacturing fields.

Note that the numerical examples presented in this chapter are based on actual data collected from a SMD manufacturing process of a global leading electronics manufacturer in Korea. The configuration of the SMC warehouse layout is shown in Figure 1. As shown in the figure, there are 30 racks in the warehouse, each of which has identical 144 bins. Total number of bins is 4,320. We consider 804 different types of

SMCs for 55 models using an SMD production plan data for a month. The frequency of usage for each material is calculated based on the production plan and the BOM information of the models.

4.1 Computational Experiment

A major characteristic of the proposed algorithm is that the insights accumulated from the experience of the manufacturing site are reflected in the initialization phase. To demonstrate the superiority of the proposed algorithm, we compare the GA results of random initialization with those of the heuristic initialization. The experiments are preformed based on the three different cases in terms of the number of materials: small, medium, and large (actual) cases. For the small and medium cases, we have selected 50 and 100 materials respectively, in order of high frequency of use. In the large case problem, all materials (804 materials) are assigned.

The hyper parameters of both proposed and general GAs are set as follows; the maximum number of generations is 5,000, the population size is 100, the proportion of elite population is 0.1, and the number of parents selected in each generation is 4. The crossover rate is 0.7 and crossover intensity is 0.2. As a crossover method, the single-point crossover and Davis' order crossover methods are applied at the rate of 0.5 and 0.5 respectively, with a parameter of 0.3 for the one-point crossover and a parameter of 0.4 for the Davis' order crossover. The random swap mutation is implemented with a rate of 0.05. The termination condition is satisfied when the number of generations have reached to the maximum number of generation. Each case is replicated 10 times to compare the result from each algorithm. The algorithms are implemented in Python with Windows 10, Intel(R) Xeon(R) W-2123 CPU @ 3.60GHz, and 48GB RAM.

Figure 4 shows the boxplot of the fitness values for each case. In Figure 4 (a), there is no significant difference between the results of the two algorithms for the small case. For the medium size case shown in Figure 4 (b), we can see that the proposed algorithm gives slightly improved results than the general GA, although the difference in results is not as noticeable as that in the small case. It implies that the general GA can be considered as a suitable solution approach for the storage assignment problem with small and medium-size instances. However, unlike the two preceding cases, the difference between the results of the proposed algorithm and the general GA is significant for the large size case as shown in Figure 4 (c). Despite the curse of dimensionality, the proposed algorithm gives much better results than the general GA, whereas the performance of the general GA deteriorates dramatically. This demonstrates that the proposed heuristic initialization works efficiently to solve the industry-sized storage assignment problems.

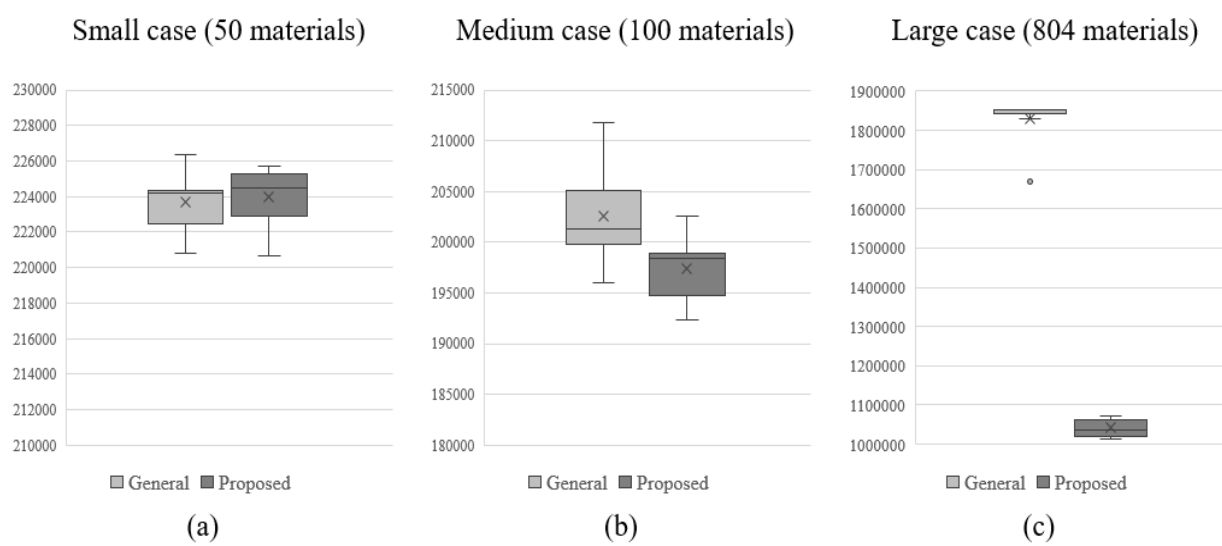

Figure 4: Boxplot of fitness values.

In terms of computational time, it takes 179 seconds in average for the small cases, 308 seconds for the medium cases, and 1,966 seconds for the large cases. Since we set the termination condition as the maximum number of generation in GA, the computational time of the algorithm is approximately linear to the size of the instances. We also analyzed the convergence of the proposed algorithm. For the small-sized instances, it takes an average of 36 seconds and 1,012 generations for convergence. For the medium-sized instances, the algorithm proceeds on average 1,455 generations to converge and takes 89 seconds. For the practical-sized instances, it takes an average of 507 seconds with 1,283 generations to converge. Although there were some deviations in convergence time due to the probabilistic behavior of the algorithm, the trend of the convergence time is also proportional to the size of the instance. Since the material allocation decision in the warehouse is typically occurring on a weekly or monthly basis, the computation time of our algorithm is considered to be suitable for use in the field operation.

4.2 Simulation Experiment

To validate the result of the proposed algorithm, we developed a simulation model using AutoMod based on the real-world layout and working time data. AutoMod is one of the most popular commercial simulation softwares widely used in production and logistics fields. Figure 5 shows the layout of the warehouse in AutoMod simulation that we made by reflecting the characteristics and behaviors of the real-world warehouse site.

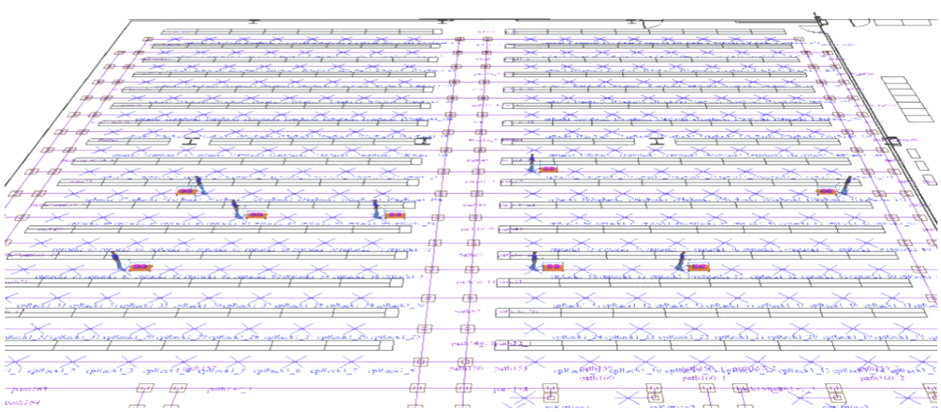

Figure 5: Layout of the warehouse in AutoMod.

The results of the material location assignment from the following three benchmark policies are compared with those from the proposed assignment method.

- *Benchmark 1* (BM1): Simple-sorting policy (sorting by material code)
- *Benchmark 2* (BM2): Frequency of material (sorting by material frequency)
- *Benchmark 3* (BM3): Frequency of model (sorting by model and material frequencies)

The simulation experiments are conducted with the actual production data acquired for 20 working days in February 2020. Additional operation data such as the picking time, the worker's walking speed, and the congestion time were measured and the average values are applied deterministically to the simulation model. The performance measure of the simulation experiment is the daily picking distance, which is directly related to the efficiency of the SMC storage placement.

Figure 6 describes the result comparison in the daily picking distance from the simulation experiments. As shown in the figure, the daily picking distances with the proposed storage assignment outperforms those with the benchmark assignments. For all dates, the picking distance is in the order of BM1 > BM2 > BM3 > proposed algorithm. It is obvious that BM1 gives the worst results because it does not take into account the material priorities. The only advantage of this policy is that it provides convenience in storage management. Both BM2 and BM3 give the better results than BM1 as considering the frequency-based material priorities.

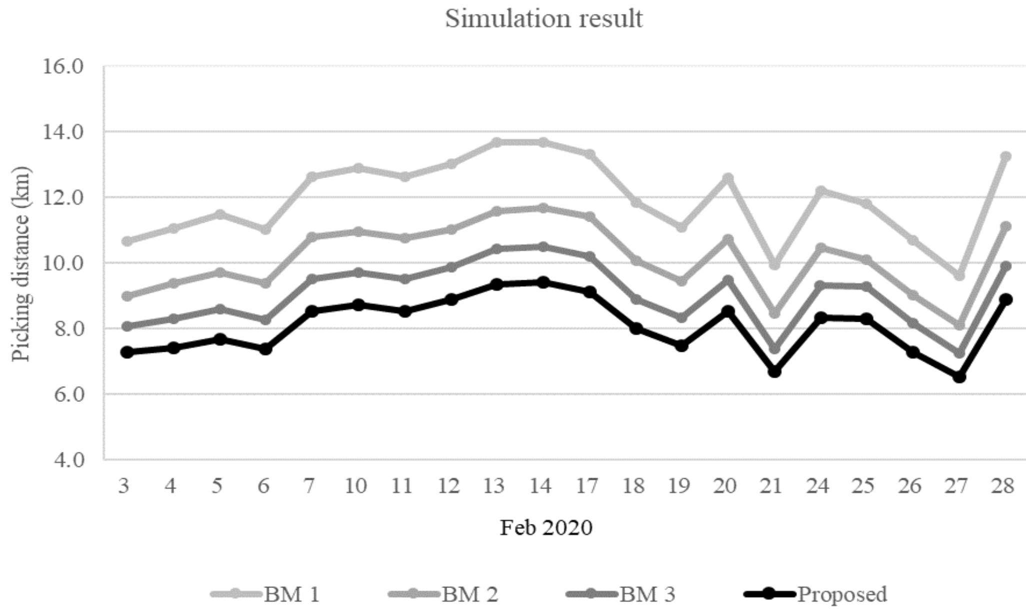

Figure 6: Simulation result of daily picking distance in Feb 2020.

The proposed storage assignment can reduce the picking distance by 32%, 20%, and 10% compared to BM1, BM2, and BM3, respectively. It is especially noticeable that the proposed approach further improves BM3, which has been considered to be one of the most reasonable and logical assignment approaches for the SMC storage assignment in practice. The results give significant implications from a management perspective in that the improvement in the picking distance leads to the reduction of the workload of the logistics resources such as workers or retrieval robots.

5 CONCLUSION

In SMD manufacturing, over a hundred of different types of SMCs are required to be provided to each production line. This study introduces the storage location assignment problem in SMC warehouse and proposes a mathematical programming model that minimizes the sum of the SMC picking distance considering the production plan and the BOMs. To efficiently solve the problem, we apply GA by reformulating the storage location assignment problem as a storage location ordering problem. We generate the initial population based on the properties of SMCs so that the GA can quickly converge to the best chromosome. Computational experiments show that the proposed heuristic initialization works efficiently to deal with the industry-sized problems, and it leads to improvements in picking distance compared to the existing methods. The contribution of our study is twofold. First, we introduce the problem of determining the location of material storage in SMD manufacturing. Second, we present heuristics to create initial population by utilizing practical problem characteristics. Our proposed method of storage assignment can practically improve not only the traditional warehouse operation where the workers pull trolleys to pick materials, but also the operation of fully automated warehouse system. As future studies of this paper, we would consider the material put-away process at the warehouse in the storage decision model. We would further improve the efficiency of the warehouse operation by redesigning the layout considering the put-away and picking movement of the materials.

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