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A SIMULATION-BASED SEQUENTIAL SEARCH METHOD FOR MULTI-OBEJCTIVE SCHEDULING PROBLEMS OF MANUFACTURING SYSTEMS

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ABSTRACT

A scheduling method based on a combination of dispatching rules is often used in dynamic and flexible manufacturing systems to consider changing production environments. A weighted sum method, which assigns weights to dispatching rules and selects the job that has the largest weighted sum as the next job, is frequently used in LCD or semiconductor manufacturing systems. The weights of dispatching rules in each process stage are determined by fab engineers and adjusted periodically to reflect the current state of the system. Fab engineers choose appropriate weights based on their experiences to improve multiple objectives, such as maximization of throughput and minimization of setup times simultaneously. In this study, we propose a systematic sequential search method for dispatching rule weights to provide Pareto-front solutions. The proposed method divides a search space into sub-spaces with decision tree methods generated for each objective and also uses surrogate models to estimate objective values.

1 INTRODUCTION

LCD fab lines are mostly composed of multiple process stages where each stage has parallel machines and a buffer, and jobs are processed sequentially in those stages and visit some stages multiple times. Many of LCD or semiconductor manufacturing systems are operated with dispatching rules due to dynamic production environments with uncertain arrival time of jobs, variable processing times, and machine breakdowns. However, using a simple dispatching rule, such as shortest processing time (SPT) or earliest due date (EDD), does not guarantee a high performance. Hence, fab engineers have designed specialized dispatching rules by considering the characteristics of fab lines and used them together to determine a job sequence. There are typically two approaches for using multiple dispatching rules, a priority-based method and a weighted sum method. In the priority-based method, dispatching rules are sorted based on the order of their priorities given by engineers, and a job is selected by the highest priority rule. When ties occur, the next highest priority rule chooses a job to be processed (Lee et al. 2018). The weighted sum method, however, computes a priority score of each job by multiplying a certain value of a job given by each dispatching rule by the weight of the dispatching rule and then adding the values from all dispatching rules.

The job with the highest score is chosen to be the next job (Dabbas et al. 2001; Zhang and Rose 2013). The weighted sum method is considered to be more effective than the priority-based approach because it considers more features from all dispatching rules in determining a sequence of jobs. Therefore, LCD fab lines in Korea mostly use the weighted sum method in operating manufacturing systems (Lee et al. 2019).

The weights of dispatching rules are adjusted by the fab engineers periodically (usually once or twice in a 8-hour shift) to reflect both production environments and multiple objectives, which can change from time to time. Even if there are some changes in production environments such as work in process (WIP) or the number of available machines, the weight set does not change dynamically because small changes in a weight set can affect the throughput or setup times significantly. Therefore, engineers check objectives in their operation shift, determine a weight set and monitor the production data. Engineers mostly rely on their previous experience or know-how in determining the weights because historical operational data do not sufficiently reflect the current dynamic shop floor, which requires a systematic search method that can provide a weight set within a short period of time while considering the current production circumstances. Therefore, we develop a method which can search weights of dispatching rules with a small data set when multiple objectives are considered simultaneously.

There have been numerous studies on hybrid flow shop or job shop scheduling with reentrant flows which correspond to the LCD manufacturing system. Cho et al. (2011) proposed Minkowski distance-based Pareto genetic algorithms with a local search strategy for the bi-objective function of makespan and total tardiness. Cho et al. (2017) also addressed reentrant hybrid flow shop scheduling by developing a two-level method to improve productivity and customer satisfaction. Ahmadi et al. (2016) used two genetic algorithms, NRGA and NGSA-II, for flexible job shops in order to optimize stability and makespan, and provided a set of Pareto-front solutions. These algorithms require a large number of evaluation processes, whereas the number of data points that can be sampled in this study is very small. It usually takes several minutes to obtain a production schedule of an entire manufacturing system with given weight sets of dispatching rules, by simulation. In a TFT-LCD fab line where each process stage uses three to six dispatching rules, it takes about 6-7 hours to generate 100 three-day schedules when using MozArt, which is a simulation-based scheduling program for semiconductor or other manufacturing systems (Lee et al. 2018). Moreover, it is not easy to apply those genetic algorithms when production environments keep changing.

There have also been some studies on dispatching rule-based methods for flexible flow shops or job shops with multiple objectives. Dabbas et al. (2001), Dabbas and Fowler (2003), and Dabbas et al. (2003) proposed a scheduling approach, which combines multiple dispatching rules into a single rule, to optimize multiple objectives for scheduling problems of semiconductor manufacturing systems. They approximated target objective functions using the a simplex centroid design method and the response surface methodology. The simplex centroid design method is one of the techniques for sampling that makes the sum of weights for a stage equal to 1. The objective functions considered in the studies are transformed into desirability functions, which are then combined into a single objective function, called total desirability. Hence, the proposed approach provides only one schedule, not a Pareto-front, with a high performance on average to fab engineers. Also, 16,129 (=127^2) simulations are required to apply the simplex centroid design method to our problem, considering two process stages each of which uses 7 dispatching rules.

Lee et al. (2019) provided a decision tree-based sequential search method that can provide a weight set of dispatching rules with an assumption of a single objective. We extend the previous study in Lee et al. (2019) by considering multiple objectives.

We propose a sequential search method for flexible flow shop scheduling with reentrant flows in order to optimize multiple objectives by assuming the weighted sum method. The proposed method narrows the range of a search area by dividing it into a sub-spaces with decision tree models, and samples more data points in those sub-spaces. It then provides Pareto-front solutions.

2 PROBLEM DESCRIPTION

We consider a TFT-LCD fab line that is operated with the weighted sum method of multiple dispatching rules. The fab line consists of multiple process stages, each of which has several parallel machines and a different set of dispatching rules. There are multiple job types, each of which has a large number of jobs. Jobs consist of multiple operations that have to be executed in a given order. We assume that all jobs have the same operation sequence. Jobs visit some stages repeatedly, and hence some operations are conducted on the same process stage. We distinguish operations that are performed in the same stage by the number of times that jobs visit the stage. Setups occur when a job type or an operation is changed on a machine.

A dispatcher of each stage contains the dispatching rules used in the stage and assigns certain priority values between 0 and 1 to jobs, waiting in the buffer of the stage, for each dispatching rule. It then computes a priority score of each job with a given weight set of dispatching rules and selects the job with the highest score for processing. Ties are broken with the first-in-first-out (FIFO) rule. The procedure of determining a job sequence with a dispatcher is described in Figure 1.

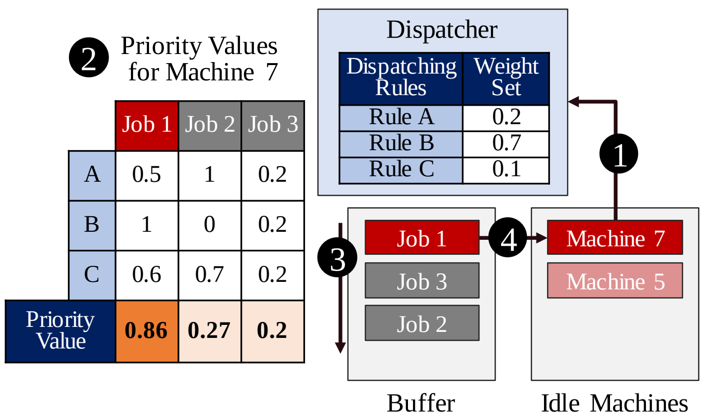


Figure 1: Dynamic job assignment of a dispatcher (Lee et al. 2018).

In Figure 1, machine 7 is idle and jobs 1, 2 and 3 are waiting in a buffer. The process stage is assumed to use dispatching rules A, B and C, and a weight set of (0.2, 0.7, 0.1) is given. Suppose that the three dispatching rules assign 0.5, 1, and 0.6 to job 1, respectively, for machine 7. Then the priority score of job 1 is 0.86 (= 0.5×0.2+1×0.7+0.6×0.1), and similarly, jobs 2 and 3 have the scores of 0.27 and 0.2, respectively. Therefore, the dispatcher allocates job 1, which has the highest priority score, to machine 7.

The dynamic scheduling method based on the weighted sum method is implemented in the MozArt which is a simulation-based scheduling program used in several semiconductor and LCD manufacturing fabs in Korea (Ko et al. 2013). Hence, we use a TFT-LCD fab line model constructed by the program for evaluating solutions with the weighted sum method. The model has 10 process stages and 70 machines in total, and each stage has a different number of parallel machines. There are 11 job types and they have the same operation sequence which consists of multiple reentrant flows. In practice, the photo-lithography process is a bottleneck, and dry etching and wet processes, which are located in front of the photo-lithography process, are also important. Therefore, we apply the proposed sequential search method for the three process stages while assuming that the other stages follow the FIFO rule.

The dispatchers of the photo-lithography, dry etching, and wet process stages use 7 dispatching rules, which are described in Table 1. We note that the dispatching rules in Table 1 have been developed by fab engineers. The four dispatching rules, Min Move Quantity (MMQ), First in First Out (FIFO), Proportion Jot Type (PJT), and Target Delay (TD) rules have been used in a TFT-LCD model of Lee et al. (2019), and the other three, Max Move Limit (MML), No Setup (NS), and Process Balance (PB) rules, are newly introduced in this study. The MML rule is similar to the MMQ rule, which encourages the consecutive processing of jobs of the same type. However, they limit the maximum number of jobs of a certain type that can be operated consecutively because the quality of jobs may deteriorate by using the machine for a long time (He et al. 2000). The PB rule considers the number of jobs waiting for the same operation, and the PJT rule is similar to PB but further considers the number of jobs of the same job type.

We consider a periodic scheduling policy in which a set of weights is adjusted periodically, usually once or twice in a shift. Therefore, the duration of searching weights is limited. The proposed search method suggests proper weight sets for all of the dispatchers by considering multiple objectives and dynamic production environments. We consider the movement and setup times of the photo-lithography stage as the objectives and assume that the buffer capacity in each stage is not limited. We also assume that dry etching and wet process stages use the same dispatcher, which means that the same weight set is used for the two stages.

Table 1: Dispatching rules for the TFT-LCD fab line.

Dispatching Rule	Description	Score Type
First in First Out (FIFO)	Assign a large value to a job that arrives earlier than others.	continuous
Max Move Limit (MML)	Assign 1 to a job if the job has the same job type and operation as the last job's type and operation on the machine, respectively, and if the number of jobs that have been processed since the last setup on the machine is smaller than a certain value (1000).	binary
Min Move Quantity (MMQ)	Assign 1 to a job if the job has the same job type and operation as the last job's type and operation on the machine, respectively, and if the number of jobs that have been processed since the last setup on the machine is smaller than a certain value (500).	binary
No Setup (NS)	Assign 1 to a job if the job type does not cause any setup.	binary
Process Balancing (PB)	Assign a large value to a job if there are many jobs waiting for the same operation as the job's.	continuous
Proportion Jot Type (PJT)	Assign a large value to a job if there are many jobs of the same job type as the job's, and many jobs among them are waiting for the same operation as the job's.	continuous
Target Delay (TD)	Assign a large value to a job if it is urgent.	discrete

3 SEQUENTIAL SEARCH METHOD FOR MULTIPLE OBJECITVES

The whole procedure of the proposed method is described in Figure 2. The numbers in the boxes in Figure 2 indicate the corresponding sections. It first divides an entire search space of weights into several sub-spaces by overlapping the ranges determined from decision trees and selects promising sub-spaces. It then samples and evaluates more weight sets from those selected sub-spaces and divides the search space again based on the sampled data. These steps are repeated for a given number of iterations, I, and then Pareto-front solutions are provided to fab engineers among the weight sets sampled. We denote h^i and H^i as a sub-space and a set of sub-spaces divided in iteration i, respectively, and G^i as a set of selected sub-spaces in iteration i.

There are three hyper-parameters, an initial sampling size, m^0, the number of total iterations, I, sampling size in iteration i, m^i. They are determined by considering the total number of samples (or simulations), $M = \sum_{i=0}^{I} m^i$, which can be selected within the limited duration. We describe each step of the method in detail from Section 3.1 to Section 3.6.

3.1 Initial Sampling

We assume that there is no information on the relationship between dispatching rule weights and objectives. Hence, the proposed method samples m^0 weight sets that are evenly distributed and unbiased over the entire search space by using an optimal Latin hypercube sampling (OLHS) method (Park 1994). The OLHS method is applied to each process stage independently so that the three stages have a different set of weights. Finally, the weights are scaled to have the sum of weights of 1 in each stage.

3.2 Objective Values Evaluation with Simulation

After generating weight sets in Section 3.1 (or Section 3.6), the objective values, movement and setup times, of each weight set are computed by MozArt with the weighted sum method.

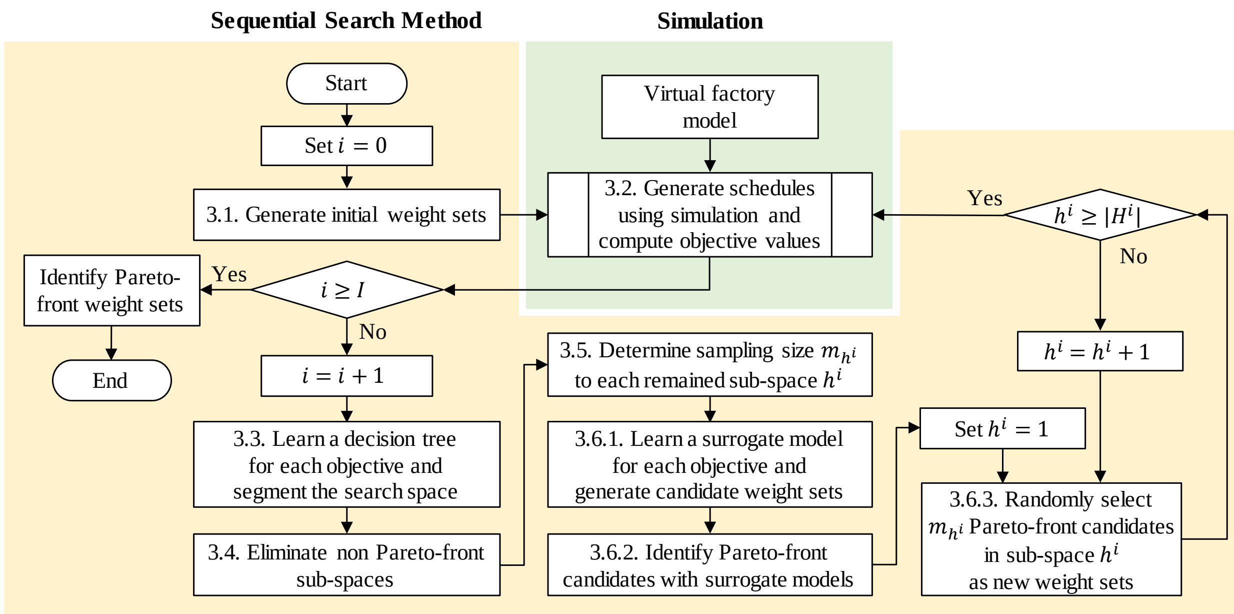


Figure 2: The entire sequence of the proposed sequential search method for multiple objectives.

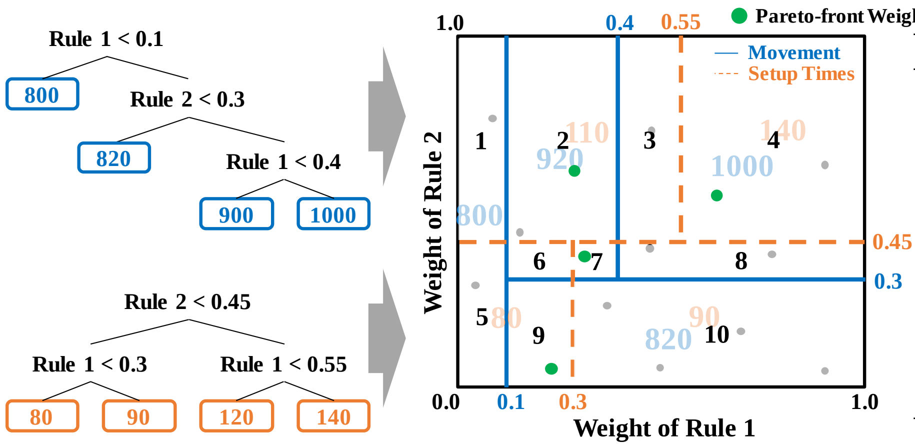
3.3 Search Space Segmentation with Decision Trees

Since the time to determine a weight set of dispatching rules is limited, it is necessary to focus on a small portion of the entire search space. In this step, promising sub-spaces are identified with a decision tree method, and new weight sets are sampled from those sub-spaces in Section 3.6. The sub-spaces divided from the decision tree of each objective are overlapped, which then generates a new set of sub-spaces as illustrated in Figure 3. Two objectives and two rules, Rule 1 and Rule 2, are assumed in Figure 3. We can see two decision trees generated for each objective in Figure 3(a) and the sub-spaces divided based on the decision trees in Figure 3(b). By overlapping the boundary lines in Figure 3(b), 10 sub-spaces are newly generated as in Figures 3(b) and (c) ($|H^i| = 10$). Each objective value of sub-space h^i in Figure 3(c) indicates the average movement and setup times of weight sets sampled from the sub-space h^i.

The proposed method uses a basic decision tree algorithm, CART (Breiman et al. 1984), which generates branches in a tree by using the sum of variations of training data, and Table 2 shows the input variables used for generating a tree to improve the accuracy (Dabbas et al. 2001), 98 input variables in this study. We note that weight sets sampled so far are all used for generating the decision tree.

3.4 Sub-space Elimination

The proposed method now identifies some sub-spaces that are likely to have good solutions. We select sub-spaces, in H^i, which already have Pareto-front weight sets and then constitute G^i from those chosen sub-spaces. For example, in Figure 3(b), G^i contains sub-spaces 2, 4, 7, and 9 because they have Pareto-fronts denoted as the green dot. In addition, sub-spaces 6 and 8 can also be added into G^i because their mean objective values in Figure 3(c) become Pareto-fronts, which may imply that it is worth searching in sub-spaces 6 and 8 further. We will later compare the two selection rules, (SR1) one choosing sub-spaces that have Pareto-front weight sets and (SR2) another selecting sub-spaces where mean objective values are Pareto-fronts.



h^i	Movement	Setup Times
1	800	110
2	920	110
3	1000	110
4	1000	140
5	800	80
6	920	80
7	920	90
8	1000	90
9	820	80
10	820	90

(a) (b) (c)

Figure 3: Example of dividing search spaces with two decision trees.

Table 2: Input variables of a decision tree.

Variable	Description	Number of Variables
w_r^k	Weight of each dispatching rule	14
$w_{r_1}^k / w_{r_2}^k$	Ratio of two weights in the same process stage	42
$w_{r_1}^k \times w_{r_2}^k$	Multiplication of two weights in the same process stage	42

3.5 Sampling Size Determination

The proposed method now assigns sampling size, m_{h^i}, for each sub-space h^i in G^i by considering the mean objective values of the sub-space. The min-max normalization method is first applied in order to adjust the scales of objective values for all of the sub-spaces in H^i. Then sampling ratio, $s(h^i)$, of sub-space h^i in G^i is computed by

$$s(h^i) = \phi_N(h^i) / \sum_{h^i \in G^i} \phi_N(h^i), \tag{1}$$

where $\phi_N(h^i)$ is the sum of the normalized objective values of sub-space h^i. The sampling size, m_{h^i}, is then determined by multiplying the sampling ratio, $s(h^i)$, and the total number of new samples in iteration i, m^i. Other sub-spaces which are not in G^i have m_{h^i} of zero.

3.6 Weight Set Generation

Since it is not possible to obtain objective values of a large number of weight sets, a surrogate model is instead developed for each objective by using the random forest (RF) technique (Breiman 2001). The surrogate model can provide an estimated objective value easily for each weight set, and a large number of weight sets can be evaluated quickly. Then potential Pareto-front weight sets obtained from the surrogate models are actually sampled and evaluated with simulation. The RF technique uses the same input variables in Table 2. After the surrogate models are derived, $10m^i$ samples of weight sets, which are randomly generated from sub-spaces in G^i, are evaluated with the models. The parameter ,$10m^i$, was determined from the preliminary experiments. The sum of weights in each process stage is also 1.

4 EXPERIMENTAL RESULT

4.1 Experimental Environment

We use the TFT-LCD fab line model constructed by MozArt. As we mentioned, there are 10 process stages and 70 machines. The photo-lithography process stage is the bottleneck, and the photo-lithography, dry etching, and wet process stages have 10, 8, and 5 machines, respectively. The average demand for 11 job types on a day is 21,734, and the model has 15,072 jobs in all buffers at the beginning. All jobs follow the same operation sequence, which consists of 26 operations. Jobs visit the photo-lithography stage five times, wet stage four times, and dry etching stage three times. The scheduling period is three days. The number of simulations (= the number of sampled points) that can be run is set to 100, 200 and 300 due to the time limit. We use m^0= 20, m^i = 16 , I = 5 for 100 simulations, m^0= 40, m^i = 20 , I = 8 for 200 simulations, and m^0= 100, m^i = 20 , I = 10 for 300 simulations. We note that it takes an hour to run 100 simulations (3 hours for 300 simulations) for the simplified model on a PC with an Intel(R) Core(TM) i7-9700 3.0 GHz processor with 32Gb RAM.

4.2 Performance Measures for Multiple Objectives

We use three measures, to evaluate Pareto-front weight sets, W, obtained with the proposed method, which are the cardinality of weight sets, hypervolume indicator, and coverage. The cardinality of weight sets, $|W|$, is the number of Pareto-front weight sets. The hypervolume indicator is the size of the objective value space covered by the Pareto-front weight sets and a reference point (Zitzler and Thiele 1998). When we consider two objectives, obj1 and obj2, each weight set, w, covers a rectangle area defined by the point (f_1^*, f_2^*) and $(f_1(w), f_2(w))$ where (f_1^*, f_2^*) is a reference value set determined by users and $f_1(w)$ and $f_2(w)$ are the values of obj1 and obj2 with w, respectively. The rectangle area then has (f_1^*, f_2^*), $(f_1^*, f_2(w))$, $(f_1(w), f_2^*)$, and $(f_1(w), f_2(w))$ as vertices. The union of $|W|$ rectangles becomes the space covered by the proposed approach. We use the reference set of (123,200, 41,800) for movement and setup times. If the weight set with $(f_1(w), f_2(w))$ of (124,000, 41,700) is considered, the covered area has the size of $800 \times 100 = 80{,}000$. The larger the hypervolume indicator is, the more the objective space is covered. When the hypervolume is similar, the large cardinality of Pareto-fronts is better because we can provide fab engineers more alternatives. The coverage measurement is used when two sets of Pareto-fronts, W_A and W_B, are compared as follows:

$$C(W_A, W_B) = \frac{|\{w_b \in W_B; \exists w_a \in W_A : w_a \succcurlyeq w_b\}|}{|W_B|}, \quad (2)$$

where $w_a \succcurlyeq w_b$ means that $f_1(w_a) \geq f_1(w_b)$ and $f_2(w_a) \geq f_2(w_b)$ in the maximization problem, which can be said that weight set w_a dominates weight set w_b (Zitzler and Thiele 1998). The coverage function C provides a value between 0 and 1. When it is close to 0, then W_B is better.

4.3 Experimental Results

We consider the combination of the factors for the sub-space elimination and weight set generation. For eliminating sub-spaces, which are not likely to have Pareto-optimal weight sets, the proposed method has two types of criteria for selecting good sub-spaces, SR1 and SR2. Also, we use the RF technique as a surrogate model of the entire search space as explained in Section 3.6. We compare the results of the combination of those factors.

Table 3 shows the results. We denote C1 and C2 as the proposed search approach with SR1 and SR2, respectively, for the sub-space elimination. C3 indicates the approach applied with both SR1 and SR2. C1, C2, and C3 only generate new samples randomly without the RF models. C4, C5, and C6 in Table 3 are similar to C1, C2, and C3, respectively, but RF models are applied to them for generating new samples. The final approach, C7, does not use sub-space segmentation or elimination, and RF models are applied to generate weight sets for each iteration. With C7, if the number of potential Pareto-front weight sets, m^i_{C7}, which are identified by the RF models, is smaller than m^i, $m^i - m^i_{C7}$ samples are selected among $10m^i - m^i_{C7}$ weight sets.

The proposed method is run 20 times, and the average value is presented in Table 3 with 100 simulations. We can see that the hypervolume and cardinality of C1, C2, and C3 are smaller than those of C4, C5, C6, and also C7. Hence, it is better to use the RF model for the weight set generation. In addition, the sub-space selection may not work well without the weight set generation method. We can also see that the area covered with SR1 is larger than that of SR2.

Table 3: Experimental results (100 simulations).

Search Method Factors	Description		Hypervolume	Cardinality
	Sub-space Elimination	**Weight Set Generation**		
C1	SR1		1.366×10^8	5.10
C2	SR2	-	1.303×10^8	4.95
C3	SR1, SR2		1.296×10^8	5.40
C4	SR1		$\mathbf{1.398 \times 10^8}$	5.10
C5	SR2	RF	1.366×10^8	5.55
C6	SR1, SR2		1.371×10^8	5.60
C7	-	RF	1.387×10^8	**5.95**

With 100 simulations, C7 has a larger number of Pareto-fronts than C4, but the hypervolume is smaller. The hypervolume indicator is more important in general than the cardinality to fab engineers because the weight sets selected from the large hypervolume can generate schedules with better objective values. Table 4 shows the coverage indicator of two Pareto-front sets from C4 and C7. We can see that 43.6% of Pareto-fronts from C7 are dominated by weight sets from C4, whereas 35.9% of Pareto-fronts from C4 are covered by the weight sets of C7. Therefore, weight sets from C4 are better than those of C7.

Table 4: Experimental results for coverage indicator (100 simulations).

Coverage of Two Sets	Average Value
$C(W_{C4}, W_{C7})$	0.436
$C(W_{C7}, W_{C4})$	**0.359**

We observed that SR2 does not perform well because the hypervolume sizes of C2 and C5 are smaller than those of C1 and C4, respectively in Table 3. Table 5 presents the number of sub-spaces selected by SR1 and SR2 in each iteration with C6. The fourth column, SR1∩SR2, indicates the number of sub-spaces in the intersection of sub-spaces from SR1 and SR2, and SR1∪SR2, in the fifth column, shows the total number of sub-spaces selected with C6. The average numbers of sub-spaces selected from SR1 and SR2 are 4.36 and 1.05, respectively. SR2 is not able to provide many sub-spaces. Hence, most Pareto-fronts are found from the sub-spaces selected from SR1.

The proposed sequential search method, C4, is now compared with the OLHS method and a simple random sampling (RS) method that selects weights by assuming a uniform distribution. The experimental results for the average hypervolume and cardinality of Pareto-front weight sets are shown in Table 6. We can see that the hypervolume by the proposed method is larger than that of OLHS or RS, which means that the weight sets with C4 cover a wider area than that from OLHS or RS. As the number of simulations is increased, the gaps of the hypervolume and cardinality between the proposed approach (C4, C7) and other methods (RS, OLHS) become large. The hypervolume of C7 and C4 with 300 simulations are increased by 12.62 % and 11.09 %, respectively, compared to the results with 100 simulations. We can see that the hypervolume of C7 with 300 simulations is larger than that of C4, which means that the RL models are useful in searching for new weight sets when the number of data points is larger than or equal to 300.

Table 5: The number of sub-spaces selected with C6 (100 simulations).

$\boldsymbol{i}$	**Sub-space Selection Rule**			
	SR1	**SR2**	**SR1∩SR2**	**SR1∪SR2 (= $\lvert G^i \rvert$)**
1	3.48	1.04	0.08	4.44
2	3.92	1.08	0.08	4.92
3	4.42	1.08	0.12	5.38
4	4.92	1	0.16	5.76
5	5.04	1.04	0.12	5.96

Table 6: Performance comparison.

Search Method	**100 Simulations**		**200 Simulations**		**300 Simulations**	
	Hypervolume	**Cardinality**	**Hypervolume**	**Cardinality**	**Hypervolume**	**Cardinality**
RS	1.297×10^8	5.2	1.315×10^8	5	1.334×10^8	5.35
OLHS	1.301×10^8	5.75	1.310×10^8	5.25	1.340×10^8	5.45
C7 (RF)	1.387×10^8	**5.95**	1.496×10^8	**6.87**	$\mathbf{1.562 \times 10^8}$	7.8
C4 (P1+RF)	$\mathbf{1.398 \times 10^8}$	5.10	$\mathbf{1.499 \times 10^8}$	6.5	1.553×10^8	**8.35**

5 CONCLUSION

We have developed a sequential search method that can provide proper weight sets for manufacturing systems by considering multiple objectives. The proposed method has divided the entire search space of weight sets into sub-spaces with a decision tree and overlapped the sub-spaces of all objectives. It then has searched more weight sets on some sub-spaces that already have Pareto-optimal weight sets and generated new weight sets with a surrogate model for each objective function. In the experimental results, we have showed that the proposed approach works well compared to OLHS and RS methods.

The proposed method is expected to generate a better schedule for the manufacturing systems that not only use the weighted sum method with multiple dispatching rules but also have several parameters to be determined for their operations in a short period of time. The proposed method should be further verified by considering a different layout, transfer robots, buffer size, and time window constraints. Other methods such as Gaussian process regression, can also be used in the future.

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