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A FRAMEWORK FOR PERFORMANCE ANALYSIS OF DISPATCHING RULES IN MANUFACTURING SYSTEMS

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ABSTRACT

Most manufacturing systems in which jobs arrive dynamically and their processing times have variations use dispatching rules to obtain production schedules. In LCD manufacturing, several dispatching rules that reflect the knowledge of the fab operator have been developed and prioritized to select a unique job for processing on a machine. However, engineers rank the dispatching rules based on their experiences without any systematic analysis method. Hence, there is a great need for a tool that can analyze how the order of dispatching rules affect the key performance indicators (KPIs) of schedules. Therefore, we provide a framework for the performance analysis of dispatching rules so that engineers can examine the KPIs for a given order of dispatching rules and find the best order of dispatching rules.

1 INTRODUCTION

The LCD fab line consists of TFT, CF, and Cell shops, and each shop is composed of multiple stages that have identical machines in each stage, which corresponds to a flexible flow shop (FFS). FFS scheduling problems are proven to be NP-hard (Bruno et al. 1974), and hence it takes a long time to obtain optimal solutions for large-sized instances. Therefore, many heuristic algorithms have been developed for the problem such as dispatching rules, metaheuristics, or problem-specific methods. Dispatching rules prioritize all the jobs ready to be processed and select the one with the highest priority. There are well-known dispatching rules, such as the shortest or longest processing time (SPT or LPT), earliest due date (EDD), and first in first out (FIFO) rules. They are widely used for different performance measures such as maximum completion time, lateness, and flow time. In addition, new dispatching rules that reflect the knowledge of fab engineers have also been developed and used in practice. Several dispatching rules are sometimes used simultaneously especially when multiple objectives are considered.

For LCD manufacturing in Korea, multiple dispatching rules are used with a priority policy to generate production schedules. The dispatching rule with the highest priority selects a job, and if there are many candidates that correspond to the rule, the next dispatching rules are applied in order until a unique job is chosen. Suppose that there are two rules, FIFO and EDD, and FIFO has a higher priority than EDD. Then a job that arrives at the earliest time is selected and if there are multiple such jobs, one that has the shortest due date is chosen among them. Then the job is assigned to a machine. However, the problem is that engineers rank the priority rules solely based on their experiences without any systematic analysis method. Hence, there is a great need for a tool that can analyze how the order of dispatching rules affects the key performance indicators (KPIs) of schedules. Since multiple KPIs are considered in evaluating schedules, Pareto optimal solutions, i.e., orders of dispatching rules around which there is no way of improving any KPI without degrading at least one other KPI, should be proposed.

Therefore, we provide a framework for performance analysis of dispatching rules so that engineers can examine the KPIs for a given order of dispatching rules and select the best order of dispatching rules. For the framework, we first introduce dispatching rules that are actually used in practice for LCD manufacturing. We then propose some KPIs used to evaluate the performance of schedules, such as completion time, flow time, and WIP. We use MozArt (Manufacturing operation zone by Abstract real time), developed by VMS Solutions Co., Ltd, to generate schedules and evaluate the KPIs according to the order of dispatching rules. The proposed framework is implemented with the MozArt and R programming and tested with real data from an LCD fab line.

In the rest of this paper, we review related studies in Section 2 and describe the dispatching rules and KPIs we consider in Section 3. Then we propose the framework used for the performance analysis in Section 4. In Section 5, we show the program we implemented.

2 LITERATURE REVIEW

There have been many studies on generating schedules with dispatching rules. Jeong and Kim (1998) proposed a real time scheduling methodology with simulation and dispatching rules for flexible manufacturing systems. They used well-known dispatching rules and selected an appropriate one dynamically by considering states of jobs and machines. Pickardt et al. (2010) proposed the simulation-based genetic programming for the generation of dispatching rules for semiconductor production scheduling problems. Zhang et al. (2009) integrated the simulation and response surface methodology to select appropriate rules for a semiconductor wafer fabrication system. Other studies used reinforcement learning to solve complex scheduling problems (Hal et al. 2014; Wang and Usher 2005; Wu et al. 2012).

When more than one KPI is considered, multi-objective scheduling problems with Pareto optimality have been widely examined. A point x^* in the feasible design space S is called a Pareto optimal solution if there is no other point x in the set S that reduces at least one objective value without increasing another one (Jasbir 2004). Kacem et al. (2002) defined solutions with Pareto optimality for flexible job shop scheduling with three objectives, and Deb et al. (2002) proposed a non-sorting genetic algorithm (NSGA-II) which searches for solutions near the Pareto-optimal front for multi-objective problems. Deb and Gupta (2005) searched robust Pareto optimal solutions with a genetic algorithm for multi-objective optimization problems.

Some studies have proposed frameworks for decision making in scheduling. Yan and Young (1996) proposed a decision support framework for multi-fleet routing and multi-stop flight scheduling. The framework includes several strategic models that are formulated as multiple commodity network flow problems. Falasca et al. (2008) developed a simulation-based framework to design a resilient supply chain. At the system design step, the framework helps to reduce the probabilities of disruptions and the time to recover from those disruptions and reach the normal performance in the supply chain. However, there are no frameworks or tools for the order of dispatching rules in manufacturing systems. So, we propose a framework that can help engineers understand the behavior of production systems with different priority rules based on KPIs.

3 PROBLEM DESCRIPTION WITH MOZART

MozArt is an integrated development and operations solution that can implement production planning and scheduling applications with a virtual model created by abstraction of real manufacturing factories (Ko et al. 2013). Schedules are generated with dispatching rules in MozArt as follows (refer to Figure 1):

1. When a machine becomes idle, call the dispatcher.
2. Inside the dispatcher, jobs are assigned with certain values from dispatching rules and sorted according to the top-ranked rule. Ties are broken with the next rules in order.

3. The job in the first position is assigned to the machine.

Whenever machines become idle after finishing processing, the dispatcher selects one job and assigns it to the machine. The order of dispatching rules is given by engineers.

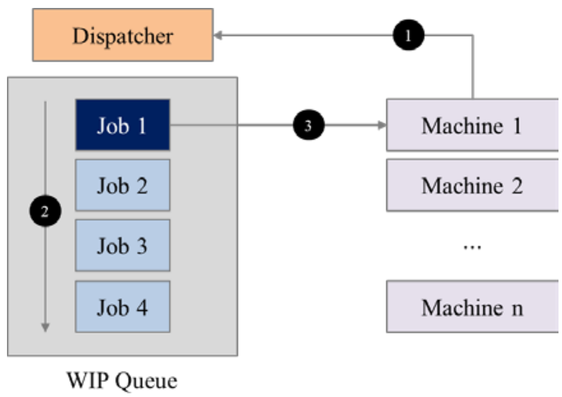

Figure 1: MozArt dispatcher process.

3.1 Dispatching Rules

We consider an LCD fab line that corresponds to an FFS. The performance of schedules for the photolithography process in the TFT shop is analyzed because it is one of the bottlenecks in the LCD fab line. In the TFT shop, jobs should go through the five process steps, as illustrated in Figure 2, each of which consists of deposition, photolithography, and etching. Hence, jobs are processed on the photolithography step five times repeatedly. There are 17 parallel machines for the photolithography process in the model, and one dispatcher is used for assigning jobs to the 17 machines. We first introduce five dispatching rules used by the dispatcher. Dispatching rules are ordered based on a given priority, and certain values from binary, continuous or discrete type of functions of dispatching rules are assigned to jobs. The detailed explanation of those functions is omitted since it is confidential. Then the job with the highest value from the top-ranked rule is selected, and if there are multiple such jobs, the other rules are applied in order until a unique job is obtained. This priority-based dispatching policy is widely used in many process stages for LCD manufacturing.

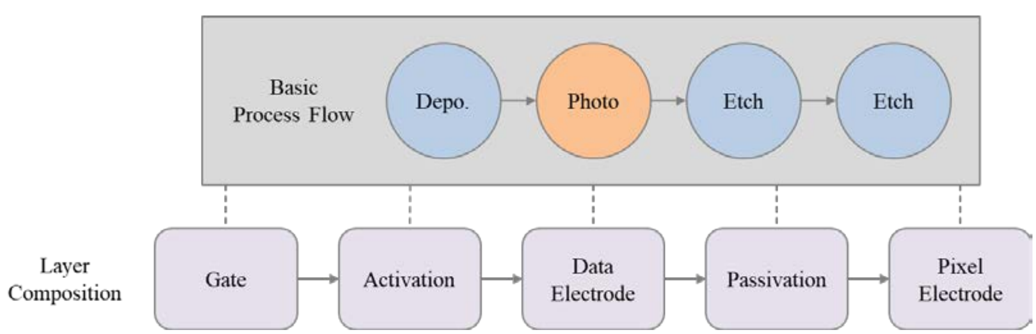

Figure 2: TFT shop process in the LCD fab line.

The dispatching rules we consider are described in Table 1. The rules have been developed by fab engineers to reflect the characteristics of the dynamic environments of LCD manufacturing. Min move quantity (MMQ) rule in Table 1 indicates the minimum number of units of a certain job type that should be processed consecutively so that setup times can be reduced. Hence, a job is given 1 if the same type of the job is being processed on a machine and the number of units processed consecutively is smaller than a target, and 0 otherwise. Prevent frequent setup (PFS) rule is to assign 1 to a job type if the number of units of the job type that stays in the buffer is larger than or equal to a given target, and 0 otherwise. The targets of MMQ and PFS rules are given by engineers. Proportion lot type (PLT) rule is similar to PFS rule, but calculates the proportion of each job type in the buffer, and assign values between 0 and 1 by considering the ratio. FIFO rule gives the highest priority to the job that arrives at the earliest time, and in target delay (TD) rule, the most urgent job receives the highest point.

Table 1: Dispatching rules for the photolithography process.

Category	Dispatching Rule	Description	Score Type
Dispatching rule	Min Move Quantity	Assign 1 to a job if the same job type is being processed on a machine.	binary
	Prevent Frequent Setup	Assign 1 to a job if the number of units that stay in the buffer is larger than or equal to a given target.	binary
	FIFO	Assign a large value to a job that arrives earlier than others.	continuous
	Proportion Lot Type	Assign a large value to a job type that has a large number of units in the buffer.	continuous
	Target Delay	Assign a large value to a job if it is urgent.	discrete

3.2 KPIs

We use eight KPIs for evaluating the schedules from different orders of dispatching rules as described in Table 2. The eight KPIs were obtained from fab engineers. Four KPIs, avg. WIP, max WIP, average flow time, and lot delay, are computed throughout the TFT shop whereas the other four KPIs are calculated only with the photolithography process. The WIP-related KPIs, max WIP and avg. WIP, should be calculated whenever there is any change in each buffer. It can also be computed as the total flow time divided by makespan.

Table 2: KPIs to evaluate schedules of the photolithography process.

Category	KPI	Description
WIP	Max WIP (units)	Maximum WIP per job type in TFT shop.
	Avg WIP (units)	Average WIP per job type in TFT shop.
Process flow time	Mean Flow Time (s)	Average flow time of jobs in TFT shop.
Equipment utilization	Utilization (%)	Average utilization rate of machines for the photolithography process
	Idle Time (s)	Average idle time of machines for the photolithography process.
Equipment setup	Number of Setups (s)	Average number of setups of machines for the photolithography process
	Setup Time (s)	Average setup time of machines for the photolithography process
Lot delay	Delayed Target (units)	The number of jobs that violate the given due dates

4 KPI ANALYSIS AND VISUALIZATION FRAMEWORK

We propose a framework to analyze the performance of schedules with different orders of dispatching rules. The framework is shown in Figure 3. First, a virtual factory model that has production information such as machines, jobs, and due dates, should be built to enable dispatching rule-based simulation. Then users determine KPIs and dispatching rules to consider. With the given information, simulations run for each different order of dispatching rules and compute KPIs for each schedule. There are two uses of the analysis tool. First, we can examine the correlation between KPIs, compare KPIs according to the top-ranked rules, and analyze the effects of each pair of rules on KPIs. Second, Pareto optimal solutions are suggested according to a given set of KPIs, and the best order of dispatching rules can be recommended by summing the weighted KPIs. The framework is applicable to other processing stages because simulations run based on a given virtual factory model and the results from the simulations are displayed.

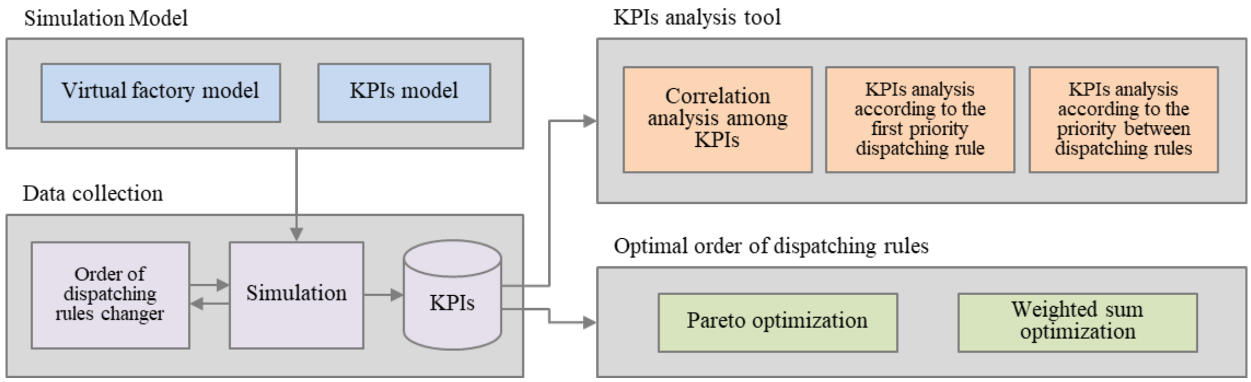

Figure 3: KPI analysis framework with multiple dispatching rules.

4.1 KPIs Analysis Tool

KPIs for each schedule are collected by MozArt, the simulation-based scheduling program. Simulations run with all possible orders of dispatching rules. The simulation period is set to 7 days which can be adjusted depending on the situation, and the total number of simulations is 120 since there are five dispatching rules. In the KPIs analysis tool, a correlation matrix and a scatter plot between KPIs are provided, so that users can understand the relation between KPIs. Next, boxplots of KPIs are given according to the top-ranked rules. Since the rule with the highest priority affects the schedule the most, we can see the impact of each rule with the box plots. Finally, each pair of dispatching rules is analyzed by comparing KPIs when one rule has a higher priority than another, and vice versa. We check whether such priority between each pair of dispatching rules affects the KPIs with the Wilcoxon singed-rank test instead of t-test since KPIs are not normally distributed. The Wilcoxon signed-rank test is a non-parametric statistical hypothesis test used to compare two samples to assess whether their population mean ranks differ. This allows users to understand the impacts of the order of dispatching rules on KPIs statistically.

4.2 Suggesting the Order of Dispatching Rules

The second function of this tool is to suggest the order of dispatching rules that can provide the desired level of KPIs. Since there are 8 KPIs considered in this study, a multi-objective optimization method should be applied to propose suitable alternatives for users. There are two applicable multi-objective optimization methods, Pareto optimization and weighted sum optimization.

Pareto optimization is a method of finding several solutions where one or more KPI values cannot be improved without decreasing a specific KPI value. The weighted sum method is to assign a weight to each KPI and provide a solution with the largest sum of weighted KPIs. The user has to provide weights to KPIs where the sum of weights is 1 in general. Since the scale of KPI values differs from one another, we normalize the collected KPIs between 0 and 1 using the maximum and minimum values. With the two optimization methods, we can select the best orders of the dispatching rules that show the good performance or satisfy the user's desired level of KPIs.

5 IMPLEMENTATION OF FRAMEWORK

We now show a prototype that is applied with real data of LCD manufacturing. The framework is implemented by using C # and R in the Visual Studio 2017 environment.

5.1 KPI Values with the First Priority Dispatching Rule

Figure 4 shows four boxplots which display four KPIs (Mean Flow Time, Delayed Target, Avg. Setup Time, Avg. Utilization Rate), respectively, according to the top-ranked dispatching rule implemented in the simulation analysis tool by MozArt. From left to right, each boxplot shows the variation of a KPI when each of the five rules, FIFO, MMQ, PFS, PLT, and TD, is set as the first priority.

When PLT rule ranks first, we can see that the KPIs are the same regardless of the next ranked rules. This means that the other four dispatching rules do not affect the KPIs because a unique job is selected with the rule. In order to reduce the average setup time, setting MMQ rule as the first one is good because the boxplot is located at the bottom, and the interquartile range is small. If FIFO rule is assigned with the highest rank, schedules with the high average setup time and a large number of delayed lots are obtained.

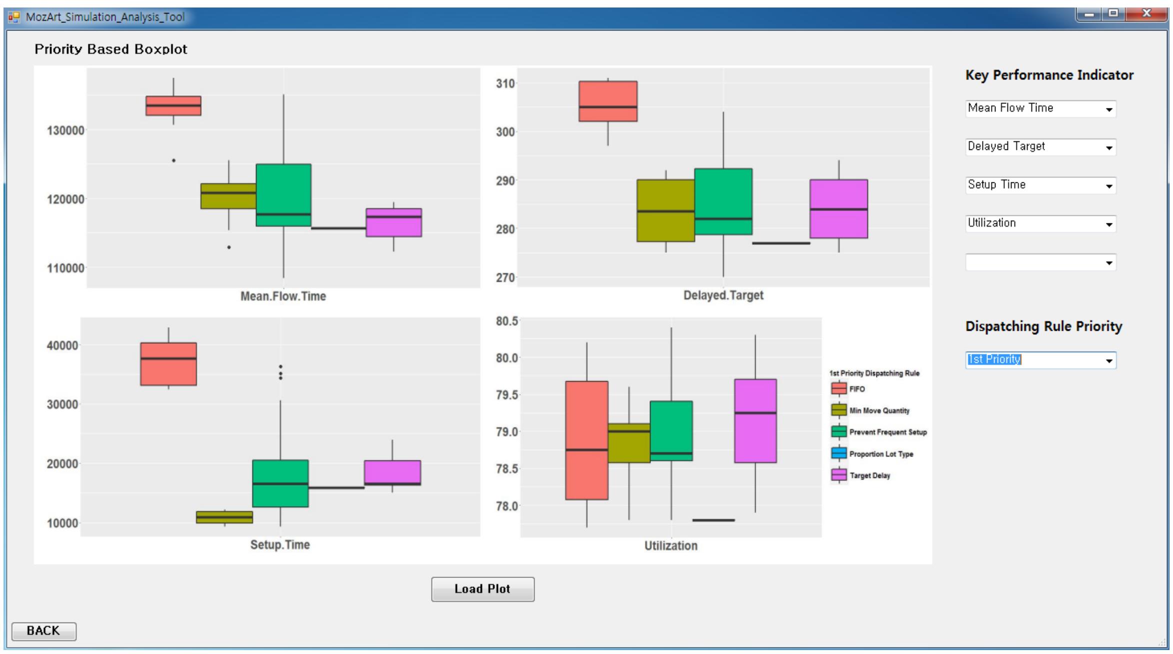

Figure 4: KPI analysis with the first priority dispatching rule.

Users can prioritize dispatching rules with these boxplots based on KPIs considered. The above boxplots only show the KPIs according to the top-ranked rules but more information can be easily shown by extending them for the second- or third-ranked rules.

5.2 Correlation Analysis of KPIs

Figure 5 shows the correlation matrix between KPIs based on 120 simulations with different orders of dispatching rules. The number in the left figure indicates the correlation coefficient of each pair of KPIs. The box in red represents a positive correlation whereas blue indicates a negative correlation. We can see that the correlation value, *r,* between the average number of setups and the average setup time is 1, which refers to a very strong correlation. Each pair of the average setup time (or the average number of setups), the number of delayed lots, and the average flow time has *r* of 0.8 or more. As the flow time of jobs decreases, the average WIP level in the buffer decreases, which can be identified from *r* of 0.89.

Users can more clearly understand the correlation from the scatter plot in the right figure. The scatter plot in Figure 5 shows the relation between the average number of setups and the average flow time of jobs. We can see that the two KPIs have a strong positive correlation. Additional analysis can be done by grouping KPIs with strong positive or negative correlations.

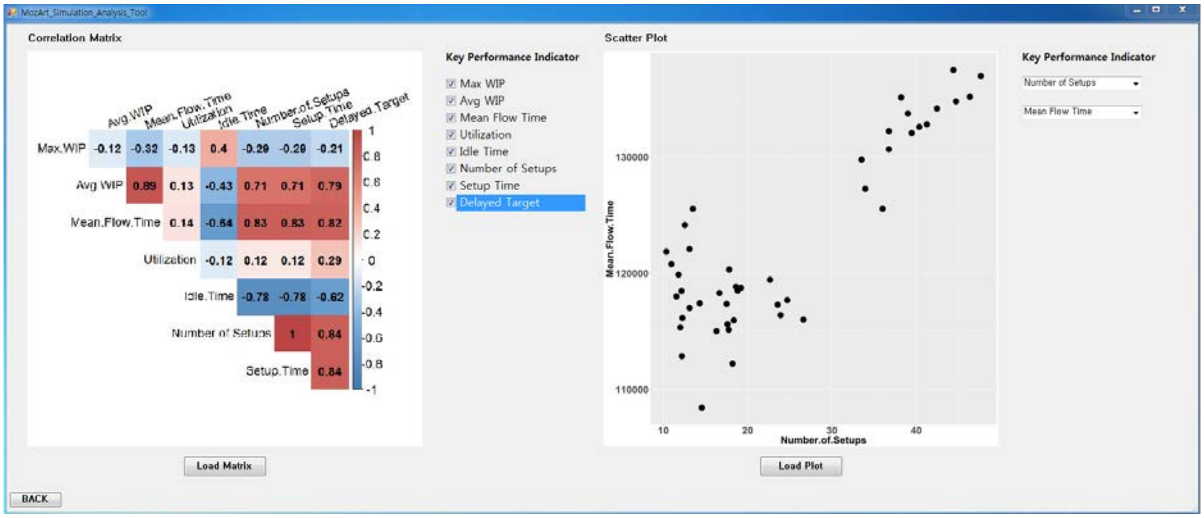

Figure 5: Correlation analysis between KPIs.

5.3 KPIs Analysis with Each Pair of Dispatching Rules

In Figure 6, a table shows how the order of two dispatching rules affects the KPIs. Each pair of dispatching rules is analyzed by comparing KPIs when one rule has a higher priority than another, and vice versa. The Wilcoxon signed-rank test is applied. The null hypothesis is that the average KPIs decrease when dispatching rule A (left) is higher in priority than dispatching rule B (right), and the values in the table are p-values from the test. The red boxes in the table indicate that the null hypothesis is rejected at a significance level of 0.005, and the blue boxes indicate that the null hypothesis is not rejected at a significance level of 0.995.

MozArt_Simulation_Analysis_Tool

Priority Based Wilcoxon Signed-Rank Test

Priority Comparison Between Dispatching Rules	Max WIP	Avg WIP	Mean Flow Time	Utilization	Idle Time	Number of Setups	Setup Time	Delayed Target
"Min Move Quantity > Prevent Frequent Setup"	0,3519	0,389	0,4361	0,178	0,0087	0,9993	0,9993	0,5168
"Min Move Quantity > Target Delay"	0,4368	0,3223	0,0359	0,893	0,1313	1	1	0,2808
"Min Move Quantity > FIFO"	0,0397	0,9999	0,9997	0,2177	0	1	1	1
"Min Move Quantity > Proportion Lot Type"	0,0988	0	5e-04	3e-04	2e-04	1	1	0,0662
"Prevent Frequent Setup > Target Delay"	0,6215	0,4476	0,092	0,8579	0,9516	0,8005	0,8005	0,4622
"Prevent Frequent Setup > FIFO"	0,0372	0,9999	0,9998	0,6532	0,0043	0,9996	0,9996	0,9998
"Prevent Frequent Setup > Proportion Lot Type"	0,0567	0,002	0,003	0,0138	0,3819	0,3195	0,3195	0,0108
"Target Delay > FIFO"	1e-04	1	1	0,4224	0	0,9997	0,9997	1
"Target Delay > Proportion Lot Type"	0,5714	0,0016	0,4465	1e-04	0,0057	0,1816	0,1816	0,0239
"FIFO > Proportion Lot Type"	0,7511	0	0	0,0268	0,9817	0	0	0

BACK

Figure 6: KPI analysis with each pair of dispatching rules.

If MMQ rule has a higher priority than other dispatching rules, KPIs related with setups, such as the average number of setups and average setup times, decrease. If FIFO rule has a lower priority than other dispatching rules, KPIs related with setups, WIP, and flow times decrease.

5.4 Suggesting the Priority Sets of Dispatching Rules

The last function of the analysis tool is to suggest orders of dispatching rules to obtain schedules with the high performance. As described in Section 4, the order of dispatching rules is provided with the Pareto optimization and the weighted sum optimization as indicated in Figures 7 and 8, respectively.

Figure 7 shows Pareto optimization solutions for the three KPIs, the average utilization rate, the average setup time, and the number of delayed lots. The KPIs used in this analysis should be selected by users. We have 120 orders of dispatching rules, and the number, 34, in the first column indicates a schedule obtained from the 34th simulation. An asterisk in the column denotes that there are more orders of rules with the same sets of KPIs, which can be identified in the tool. The five columns next to the first column, Data Point, show the order of dispatching rules, and the KPIs can be seen in the last three columns.

MozArt_Simulation_Analysis_Tool

Pareto Optimal Schedule

Data Point	Min Move Quantity	Prevent Frequent Setup	Target Delay	FIFO	Proportion Lot Type	Utilization	Setup Time	Delayed Target
"(*) P 34"	1	5	4	3	2	79,1	9855	275
"(*) P 58"	1	5	4	2	3	79,6	11790	288
"(*) P 63"	5	1	2	4	3	79,3	14670	273
"(*) P 65"	2	1	5	4	3	77,8	9315	278
"P 81"	5	1	3	2	4	80,4	36315	300
"(*) P 86"	2	5	1	3	4	80,3	14985	282
"P 93"	3	1	2	5	4	78,6	13095	270

BACK

Figure 7: Pareto optimization solutions.

Figure 8 shows the solutions of the weighted sum optimization with the weights of 0.4, 0.2, and 0.4 for each of dispatching rules used in Figure 7. The KPIs and weights should be determined by users. The normalized KPIs are multiplied with the weights, and the weighted sum is shown in the last column of the table. We can see top 10 schedules based on the weighted sum values, and the rank of each schedule is indicated in the first column of the table.

MozArt_Simulation_Analysis_Tool

Weighted Sum Optimal Schedule

RANK	Data Point	Min Move Quantity	Prevent Frequent Setup	Target Delay	FIFO	Proportion Lot Type	Utilization	Setup Time	Delayed Target	Weight Sum Value
1	"(*) P 65"	2	1	5	4	3	77,8	9315	278	0,09286
2	"P 117"	3	1	2	4	5	78	12870	275	0,1144
3	"(*) P 1"	5	4	3	2	1	77,8	15840	277	0,12198
4	"(*) P 61"	5	2	1	4	3	77,9	16920	275	0,12372
5	"P 93"	3	1	2	5	4	78,6	13095	270	0,15585
6	"(*) P 95"	2	1	3	5	4	78,7	10800	279	0,2448
7	"(*) P 113"	2	1	4	3	5	78,4	11295	284	0,25209
8	"(*) P 80"	3	5	1	2	4	78,2	20385	282	0,2571
9	"(*) P 34"	1	5	4	3	2	79,1	9855	275	0,25941
10	"(*) P 55"	5	4	1	2	3	78,7	21510	275	0,26958

BACK

Figure 8: Weighted sum optimization solutions.

Figure 9 shows the scatter plot for the Pareto optimization and weighted sum optimization solutions for two KPIs, the average setup time and the average utilization rate. Each schedule is classified by color on the graph, and the user can understand the characteristics of the optimal schedules with the graph. We can also evaluate the performance of schedules and see the differences among the schedules.

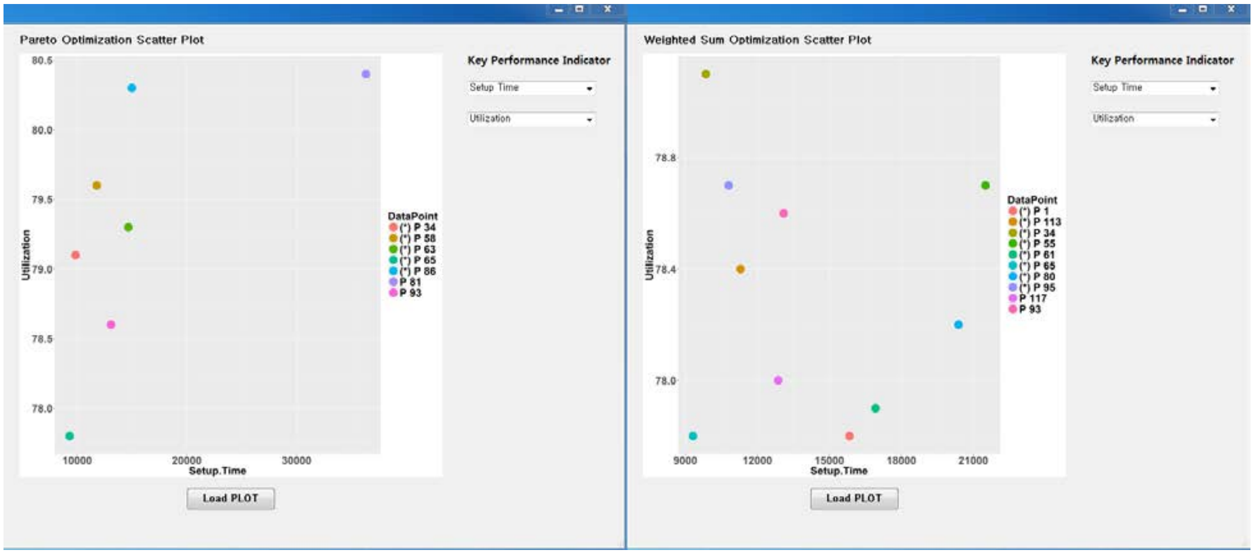

Figure 9: Scatter plots for Pareto optimization solutions (left) and weighted sum optimization solutions (right).

6 CONCLUSION

In this study, we have developed a tool to analyze and evaluate dispatching rules with multiple KPIs. We introduced several functions of the tool and showed a prototype implemented with R and Visual Studio 2017 by applying real LCD manufacturing data. We first proposed several KPIs for evaluating schedules, and introduced dispatching rules that are applied in practice. We then used statistical methods to analyze different orders of dispatching rules and KPIs. The analysis tool can suggest the best orders of dispatching rules to fab engineers for different sets of KPIs. It can improve the throughput of the fab and the efficiency of the fab operations significantly. The proposed framework can be applied to not only the LCD fab but also other dispatching rule-based processes only if a virtual factory model and KPIs are defined. We need to further extend the framework for multi-processing stages by considering different dispatching rules.

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