Proceedings of the 2014 Winter Simulation Conference
A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, eds.

NEW KEY PERFORMANCE INDICES FOR COMPLEX MANUFACTURING SCHEDULING

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ABSTRACT

Diversified and complicated manufacturing sites make optimal scheduling of production lines difficult. Under current manufacturing processes, it is almost impossible for schedulers to consider all the constraints of production processes. A strategy of simulation-based advanced planning and scheduling (APS) is employed to overcome difficulties that interfere with satisfactory on-time delivery and commitment to the current status. In simulation-based scheduling, key performance indices (KPIs) are important for selecting optimal dispatching rules in scheduling. In cases involving complex processes, in which the identification of appropriate KPIs is limited to selection among existing KPIs, KPIs should be chosen and modified carefully to optimize process management and to reflect all of the existing constraints of production. However, the existing methodologies for modifying KPIs are misplaced in complex manufacturing environments such as job-shop processes. We propose a new method to design and select appropriate KPIs that meet the characteristics of any given process, and verify with empirical analysis whether or not the KPIs meet requirements from experts of production lines.

1 INTRODUCTION

Process schedulers strive to establish realizable plans in manufacturing areas to satisfy delivery by due dates and to meet the specific goals of production plans. It is difficult for schedulers to perform realizable scheduling, however, because current manufacturing systems have progressed toward complex and diversified stages. For example, liquid crystal display (LCD) and semiconductor manufacturing processes are built on complex job-shop processes. Job-shop processes generally have multiple operation processes, which occur both concurrently and consecutively. The order and priority of the processes vary according to the kind of job (Dorndorf 1995; Blazewicz 1996).

Simulation-based advanced planning and scheduling (APS) is a strategy utilized to overcome the difficulties of scheduling job-shop processes (Ramasesh 1990). By utilizing simulation-based APS, manufacturers are able to immediately identify how the changes that come with the new orders of customers will impact the current manufacturing processes (Lee 2001). The period until a due date can be calculated by considering the current working order, together with the quantities of raw materials and inventories. Accordingly, a manufacturer obtains the ability to provide a realizable date of delivery to the customer in real time (Neely 2000). Finally, manufacturers can fulfill requests not only with respect to due dates, but also to specifications, prices, volumes, and so on, for cases in which customers place final orders with manufacturers (Kuroda 2002).

In simulation-based scheduling, dispatching rules for scheduling play a more important role than other rules (Kiran 1984; Sarin 2011). Key performance indices (KPIs) are used to select the dispatching rules appropriate for different kinds of processes. Therefore, it is critical to design and select the right KPIs. There is also a need for the ability to modify KPIs in order to satisfy constraints and requirements according to different manufacturing sites. The current existing methodologies for modifying KPIs, however, are based exclusively on the analysis of requirements by experts through the analytic hierarchy process (AHP) and Delphi (Mittler 1999; Buyurgan 2008). AHP solves different types of multi-criteria decision-making problems based on the relative priority assigned to each criteria in achieving the stated objective, and Delphi utilizes decisions from a process that relies on a panel of experts. These methodologies are suitable in cases of simple processes. In contrast, however, inappropriate KPIs are often selected due to contradictions between various requirements and realizable plans for complex processes such as job-shop processes.

Therefore, our research focuses on designing and selecting appropriate KPIs to meet the characteristics of any given process. Using empirical analysis, we also determine whether or not the KPIs meet professional requirements.

This paper is organized as follows. In section 2, KPIs used for assessing the scheduling of LCD and semiconductor processes are introduced. In section 3, our proposed methodology is discussed. In section 4, modified KPIs are assessed through empirical analysis according to whether or not the KPIs meet professional requirements. Section 5 offers conclusions and describes recommendations for further study.

2 KEY PERFORMANCE INDICES IN MANUFACTURING SCHEDULING

Schedulers use various kinds of key performance indices (KPIs) to measure performance in the manufacturing industry (Ahmad 2002). In contrast to traditional perspectives, which focus on accounting and costs, KPIs are currently used as various measures of quality, on-time delivery, inventory, and other critical aspects of manufacturing processes. Table 1 shows examples of KPIs used for manufacturing process scheduling (Ramasesh 1990; Natarajan 2007).

Table 1: KPIs of Process Scheduling.

Measurement	Key Performance Index (KPI)
Time-based measures	Mean and variance of flow time per job or operation Mean waiting time Machine idle time
Work-in-process measures	Average number of jobs in queue Value of work-in-process
Due date-related measures	Mean tardiness Proportion of jobs tardy Conditional mean tardiness Number of jobs tardy Maximum lateness
Cost-based measures	Cost of idle machines Cost of carrying work-in-process inventory Total cost per job Average value added in queue

Existing KPIs are generally used to implement post control and to evaluate process performances in most manufacturing processes (Fortuin 1988). However, simulation-based scheduling is limited to the use of existing KPIs, because KPIs in simulation-based APS determine dispatching rules and are used to implement both ex-post control and pre-control through the selected dispatching rule. In the case of LCD and semiconductor processes, there are some problems with using existing KPIs due to the complexity of the job-shop processes involved in these types of manufacturing. For example, when considering “on-time delivery,” the remaining period of time until scheduled delivery will either be short or long. Accordingly, the goal of “on-time delivery” may be achieved, regardless of the specific period of time before the scheduled date of delivery. In a real manufacturing setting, however, the shortest remaining period of time before a delivery date tends to be prioritized as the most important deadline, because the most immediate deadline affects the most jobs in subsequent steps of the process. Additionally, even in cases in which two plans involve an equivalent remaining period of time until a due date, these plans may be considered differently according to whether a production week is set to occur during the present week or in a subsequent week.

3 KPI GENERATION

Due to the reasons mentioned above, existing KPIs cannot always completely reflect the various requirements of real manufacturing sites. Each manufacturing site requires suitable KPIs, which are modified according to the unique characteristics of each site. In general, the process of identifying KPIs consists of making up lists of available KPIs, discerning suitable KPIs by using AHP and Delphi, and modifying KPIs accordingly. However, AHP and Delphi are only appropriate for simple processes. In the case of complex processes, AHP and Delphi do not take all the characteristics of the processes into consideration.

Because complex processes such as job-shop processes have a lot of constraints and various requirements, it is difficult for a manufacturing scheduler to schedule without the assistance of simulation. In other words, when it comes to scheduling, there is always a possibility of selecting inappropriate KPIs that do not meet all the requirements and constraints of complex processes. In the specific case of a big company in LCD manufacturing that uses actual simulation-based APS, the scheduler often re-modifies the scheduling results generated from simulation. This means that the requirements of the experts are not properly reflected in the simulation-based scheduling results. Accordingly, we focus on identifying discrepancies by comparing results modified by schedulers with outputs from simulation.

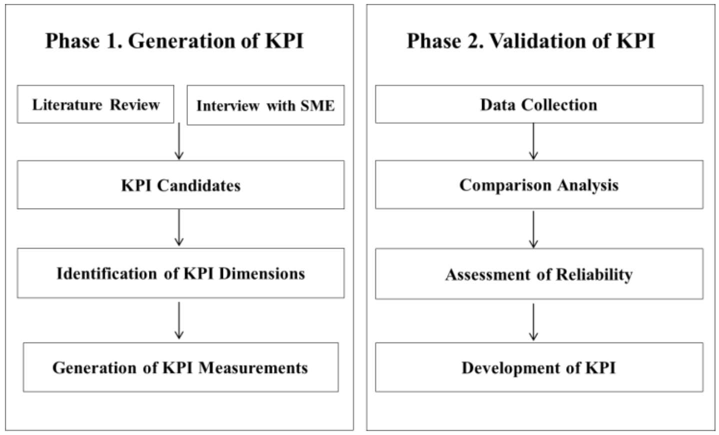

Figure 1: Framework for development of KPIs.

Our proposed method has two phases, including generation of KPIs and validation of KPIs. In the first phase, through precedent research and interviews with subject matter experts (SME), applicable KPIs and characteristics of the manufacturing processes are organized into lists. KPIs which overlap with other KPIs and have semantic dependencies are excluded from the selection of KPI candidates. We also remove KPIs that require information which cannot be obtained from simulation. The resulting KPI candidates are classified based on the dimensions of characteristics and the goals of each process. The structure of KPIs involves a two-level-hierarchy. KPI dimensions are designed to evaluate the purpose of a manufacturing process, whereas KPI measurements represent the performance of corresponding dimensions. For example, process efficiency is a dimension, and the corresponding measurement for process efficiency is capacity utilization. In the second phase of the framework, we assess scheduling reliability through comparison analysis using the data collected from real cases and the KPIs generated in the first phase. Subsequently, we proceed to identify any measurement changes reflected in the requirements of site schedulers by way of comparing simple simulation outputs and the modified results of schedulers themselves.

4 EMPIRICAL ANALYSIS

This study performs empirical analysis for a big LCD manufacturing company. An LCD manufacturing process is composed of two main sub-processes, namely, fabrication (FAB) and module (MOD) processes. The MOD process is the final stage of the LCD manufacturing process, in which LCD panels are assembled from all the parts produced in previous steps of the production process. The MOD line, which involves important processes to determine the durability and performance of LCD panels, is comprised of three procedures including a step for cleaning and polarization (CP), outer lead bonding (OLB), and final assembly (FA). Our research focuses on the OLB process, which is a bottleneck process for the production processes of LCD manufacturing in its entirety. The OLB process is a basic job-shop process, which includes a lot of constraints and requires a lot of scheduling. Scheduling of OLB processes is conducted by simulation-based APS. However, schedulers are still allowed to modify the results of simulation-based APS scheduling for OLB processes.

4.1 Simulation-based APS

Figure 2 illustrates the overall process of simulation-based APS for LCD manufacturing (Ko 2010). The process consists of three major steps. The first step, formulating the master plan (MP) from the master planning system, is divided into weekly plans via performance of a filtering simulation. Through simulation, the weekly plan is divided into daily production plans, known collectively as Plan A. Schedulers fill any gaps from new jobs into blank spots, and are thereby able to switch the order of jobs.

These requirements, however, do not take into consideration the capacity and constraints of LCD processes in particular.

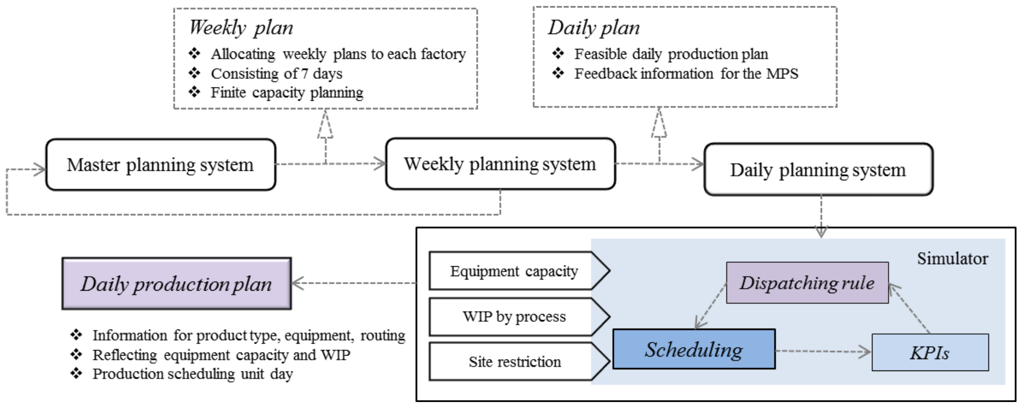

Figure 2: Simulation-based APS.

Plan A becomes Plan B through another simulation based on scheduler requirements for an alternative plan. The daily production plans of the first day and the second day are confirmed by the results of the scheduling of the previous day and the day before the previous day, which is called the pre-confirmed plan. Accordingly, these two daily production plans cannot be modified. Therefore, we focus on plans for production scheduling for the third day, known as the newly determined plan, because the plan of the day determines the production schedule after two days. The configuration of overall daily plans is shown in Figure 3.

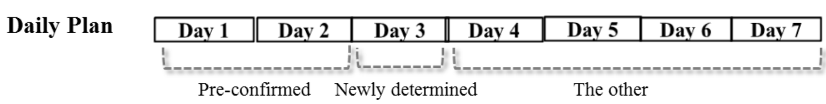

Figure 3: Configuration of daily plans.

To generate appropriate KPIs for OLB processes, all the available KPIs are considered. Available KPIs are identified based on precedent research and available data from the simulator. For example, we consider delivery due dates, amount of planned production, and work-in-process (WIP) status, as discussed in section 2. In the analysis herein, however, KPIs related to WIP are excluded, because our analysis must consider the overall process as well as the single processes involved. The KPIs associated with cost is also excluded from the selection because of the lack of cost information available from the simulator.

Experts were interviewed to reflect the requirements of the schedulers and the process characteristics in deriving KPIs. Weekly-based plans are composed of plans for the current week and the following week. Current week plans are more important than following week plans in the scheduling of OLB processes, because the order of OLB processes is linked with subsequent processes of delivery. Taking into account these details, KPI candidates are selected as follows:

- Master plan (MP) fulfillment rate
- On-time delivery
- Tardiness of residual plan
- Fulfillment rate of weekly plans
- Capacity utilization
- Job change rate
- Number of long idle times

We consider the dimensions of KPIs from the perspective of delivery due dates, because this type of bottleneck process has serious effects on the planning of other processes. Time efficiency is another important dimension. Time efficiency is an important factor in bottleneck processes, because the production quantities of an entire process are increased without wasting time per day in bottleneck processes. Our analysis focuses on two dimensions: master plan (MP) fulfillment rate and process efficiency. Master plan fulfillment rate is a dimension to evaluate the degree of achievement in a master plan. Additionally, process efficiency is defined as the extent to which a plan manages to reduce the amount of wasted time. The corresponding measurements are mapped on proper dimensions according to the characteristics of KPIs.

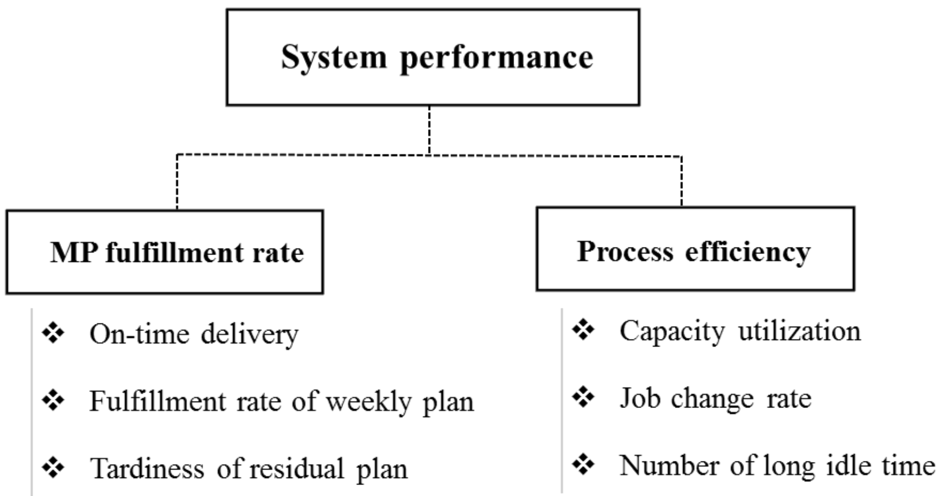

Figure 4: Hierarchy of system performance.

The final KPIs in Figure 4 include the two aspects of dimensions and measurements. According to the meaning of each dimension, the measurements to evaluate the MP fulfillment rate are composed of on-time delivery, fulfillment rate of weekly plans, and the tardiness of the residual plan. Measurements to evaluate process efficiency consist of capacity utilization, job change rate, and the number of long idle times.

4.2 KPI Measurements

This section specifically introduces six measurements that comprise on-time delivery, fulfillment rate of weekly plans, tardiness of residual plans, capacity utilization, job change rate, and number of long idle times. The selection of a past due date for delivery is equivalent to selecting an urgent plan in scheduling. Therefore, we consider the proposed framework an appropriate plan to satisfy the purposes of each KPI.

4.2.1 On-time Delivery

In a newly determined plan, on-time delivery is defined as the ratio of the planned amount satisfying the indicated date for production prior to both the delivery due date and the current week plan. High on-time delivery indicates that the number of panels scheduled in the following week is proportionately small among newly determined plans. In equation (1), D_i is defined as the on-time delivery ratio of the i th panel.

$$D_i = \begin{cases} 1 - \dfrac{T_i - S_i}{T_m - S_i} & \textit{(Due date fulfilled following week)} \\ 1 & \textit{(Due date fulfilled current week)} \\ 0 & \textit{(o/w)} \end{cases} \quad (1)$$

where T_i is the delivery due date of the i th panel, T_m is the longest delivery due date among the production of panels, and S_i is the beginning time of production for the i th panel. Therefore, the on-time delivery date in the newly determined plan is calculated by equation (2),

$$\text{On-time delivery} = \frac{1}{n}\sum_{i=1}^{n} D_i \quad (2)$$

where n is the number of panel types.

4.2.2 Fulfillment Rate of Weekly Plans

The fulfillment rate of weekly plans is a measurement that shows how many current week plans are selected from a newly determined plan. A high fulfillment rate of weekly plans implies that the number of panels scheduled in the plan for the current week takes up a large portion of the newly determined plan. The fulfillment rate of a weekly plan is defined in equation (3),

$$\text{Fulfillment rate of weekly plan} = \frac{P_D}{P_S} \quad (3)$$

where P_S and P_D are the total planned output in a newly determined plan and the week plan output in a newly determined plan, respectively.

4.2.3 Tardiness of Residual Plan

The tardiness of residual plan is a measurement that shows how many plans prior to a delivery due date are selected from the current week plan after a newly determined date. A high tardiness of residual plan means that the number of panels that are late for due dates is high among newly determined plans. The tardiness of residual plan is defined in equation (4),

$$\text{Tardiness of residual plan} = 1 - \frac{P_{ND}}{P_{NS}} \quad (4)$$

where P_{NS} is the number of panels in the current week plan after the newly determined date, and P_{ND} is the number of panels that are late for due dates in the current week plan after the newly determined date.

4.2.4 Capacity Utilization

Capacity utilization is the ratio of equipment operation time required to produce panels in a day. High capacity utilization means that the state of equipment for the majority of a day is busy, with little time wasted. Capacity utilization is defined in equation (5),

$$\text{Capacity utilization} = \frac{1}{n}\frac{\sum_{i=1}^{n} U_i}{\sum_{i=1}^{n}(24 - PM_i)}. \tag{5}$$

where U_i is the i th equipment's operation time in a day, n is the total equipment, and PM_i is the preventive maintenance (PM) time required to inspect the i equipment. Preventive maintenance (PM) time is excluded in view of capacity utilization because it is scheduled prior to production plans.

4.2.5 Job Change Rate

Job change rate is a measure of required job changes per equipment. This is an important issue in terms of process efficiency, because the time spent on switching to the production of another panel varies depending on the type of panel previously in production. Job change rate is defined in equation (6),

$$\text{Job change rate} = \frac{1}{n}\sum_{i=1}^{n} J_i. \tag{6}$$

where J_i and n are the count of job changes at i th equipment and the number of equipment, respectively.

4.2.6 Number of Long Idle Times

The number of long idle times is a count of the idle times lasting more than one hour in a day. It captures the waiting time due to job changes and equipment idle time. The number of long idle times is defined in equation (7),

$$\text{Number of long idle times} = \sum_{i=1}^{n} I_i \tag{7}$$

where I_i is the count of idle times that are more than one hour long on i th equipment.

4.3 Results Analysis

Statistical analysis was performed to determine whether there are significant differences between each version of the manufacturing plans using calculated values of KPIs for daily plans. The daily plans of Plan A and Plan B from November 1, 2013 to November 28, 2013 were used in the empirical analysis herein. The results of Plan A are obtained from simulation, and the results of Plan B are the version of the manufacturing plans amended by schedulers. For analysis of the results, the Wilcoxon signed-rank test as a non-parametric method was used, because calculated values of KPIs do not follow a specific distribution. The null hypothesis is stated as, "there is no difference between the two versions (Plan A and Plan B)," and the alternative hypothesis is "the null hypothesis is not true."

Table 2: Wilcoxon signed-rank test results.

Measurement	Median value of KPI in Plan A	Median value of KPI in Plan B	V	p -value
On-time delivery	0.9300	0.9250	94	0.0118**
Tardiness of residual plan	0.5026	0.8114	406	0.0000**
Fulfillment rate of weekly plan	0.7017	0.6730	104	0.0232**
Job change rate	**0.4135**	**0.4538**	**286**	**0.0595***
Capacity utilization	0.8186	0.9237	405	0.0000**
Number of long idle times	55.50	20.00	0	0.0000**

(*: $p < 0.1$, **: $p < 0.05$)

The null hypotheses are rejected at the level of $p = 0.5$, with the exception of job change rate, as shown in Table 2. Accordingly, it can be identified that the differences in the median values of KPIs in the two versions of plans are statistically significant. Thus in the case of the complex processes of LCD panel manufacturing, the suggested KPIs are good measurements that accurately reflect the requirements of schedulers in simulation-based APS of OLB processes.

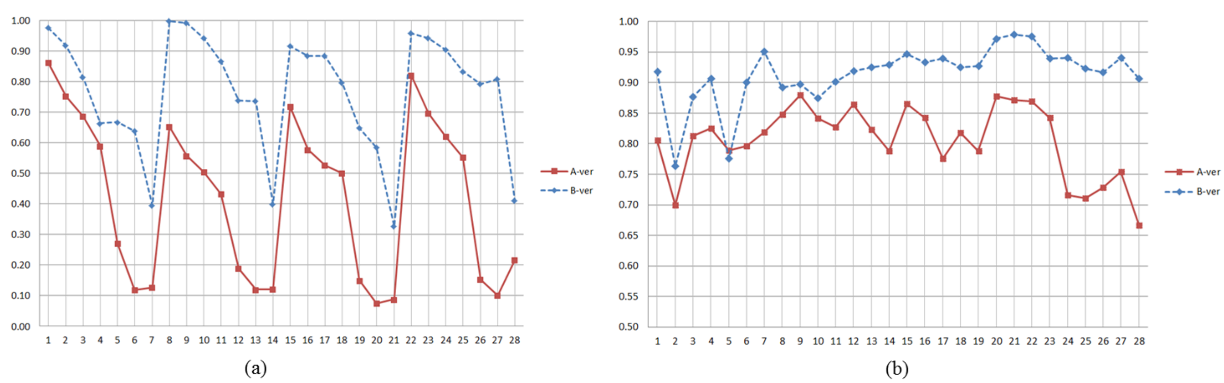

Figure 5: (a) Graph of tardiness of residual plan and (b) Graph of capacity utilization.

Figure 5 illustrates graphs of each of the KPI values for both plan versions in terms of the tardiness of residual plans and capacity utilization. The x-axis and y-axis of the graphs represent the dates of the manufacturing plans and the KPI values, respectively. Also, the solid lines and dotted lines represent the values of KPI for Plan A and B, respectively. The significant differences between plans are visually represented in Figure 5 above. Table 3 shows modifications from the schedulers when Plan A is converted to Plan B.

Table 3: Scheduler modifications in Plan B.

Modification
Jobs from the following week plan are added to Plan A
Jobs from the current week plan are fulfilled more than jobs from the following week plan for the long idle times of Plan A
Overdue jobs are added

As a result of comparison, we find that scheduler modifications of OLB processes are made according to six core measurements. The master plan fulfillment rate requires scheduler modifications in terms of adding overdue jobs and focusing more urgently on the current week plan rather than the following week plan. Process efficiency shows that schedulers reduce the long idle times of Plan A, and increase the number of jobs in the process by modifying Plan A. In spite of the modifications, however, Plan B may be impossible because schedulers are not able to consider all of the constraints incurred by changes in a real manufacturing environment. That is the reason the capacity utilization of Plan B is higher than Plan A.

CONCLUSION

We compare the outputs derived from simulation-based APS with the modifications of domain experts in a very complicated LCD panel manufacturing site. As a result of comparative analysis, we successfully propose a framework to determine where modifications are required, then apply the framework to identify appropriate KPIs. The empirical analysis also shows that the proposed KPIs do a good job of accommodating both the requirements of the site schedulers and the purposes of the tasks involved in the OLB processes of a leading LCD manufacturing company.

We will expand future research with various cases and additional experiments such as sensitivity analysis. We will also research an optimal scheduling policy by using the proposed KPIs for dispatching rules in simulation-based APS.

REFERENCES

Ahmad, M. M., and N. Dhafr. 2002. "Establishing and improving manufacturing performance measures." *Robotics and Computer-Integrated Manufacturing* 18 (3): 171-176.

Błażewicz, J., W. Domschke, and E. Pesch. 1996. "The job shop scheduling problem: Conventional and new solution techniques." *European journal of Operational Research* 93(1): 1-33.

Buyurgan, N., and C. Saygin. 2008. "Application of the analytical hierarchy process for real-time scheduling and part routing in advanced manufacturing systems." *Journal of Manufacturing Systems* 27(3): 101-110.

Dorndorf, U., and E. Pesch. 1955. "Evolution based learning in a job shop scheduling environment." *Computers & Operations Research* 22(1): 25-40.

Fortuin, L. 1988. "Performance indicators—why, where and how?" *European Journal of Operational Research* 34(1): 1-9.

Kiran, A. S., and M. L. Smith. 1984. "Simulation studies in job shop scheduling—I: A Survey." *Computers and Industrial Engineering* 8(2): 87-93.

Ko K. H., and B. C. Park. 2010. "Simulation based FAB scheduler: SeePlan®." In *Proceedings of the 2010 Winter Simulation Conference,* edited by B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, and E. Yücesan, 40-48, Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Kuroda, M., H. Shin, and A. Zinnohara. 2002. "Robust scheduling in an advanced planning and scheduling environment." *International Journal of Production Research* 40(15): 3655-3668.

Lee, H., and S. S. Kim. 2001. "Integration of process planning and scheduling using simulation based genetic algorithms." *The International Journal of Advanced Manufacturing Technology* 18(8): 586-590.

Mittler, M., and Schoemig, A. K. 1999. "Comparison of dispatching rules for semiconductor manufacturing using large facility models." In *Proceedings of the 1999 Winter Simulation Conference,* edited by P. A. Farrington, H. B. Nembhard, D. T. Sturrock, and G. W. Evans, 709-713, Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Natarajan, K., et al. 2007. "Performance evaluation of priority dispatching rules in multi-level assembly job shops with jobs having weights for flowtime and tardiness." *The International Journal of Advanced Manufacturing Technology* 31(7-8): 751-761.

Neely, A., M. Bourne, and M. Kennerley. 2000. "Performance measurement system design: developing and testing a process-based approach." *International Journal of Operations and Production Management* 20(10): 1119-1145.

Ponsignon, T., and L. Monch. 2010. "Architecture for simulation-based performance assessment of planning approaches in semiconductor manufacturing." In *Proceedings of the 2010 Winter Simulation Conference,* edited by B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, and E. Yücesan, 3341-3349, Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Ramasesh., R. 1990. "Dynamic job shop scheduling: a survey of simulation research." *Omega* 18(1): 43-57.

Sarin, S. C., A. Varadarajan, and L. Wang. 2011. "A survey of dispatching rules for operational control in wafer fabrication." *Production Planning and Control* 22(1): 4-24.

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