Workload and Delay Analysis in Manufacturing Process Using Process Mining

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Abstract. Process analysis is one of the important topics in manufacturing industry. Recently process mining has been applied to analyze manufacturing processes. In this paper we investigate the characteristics of event logs in make-to-order production and propose a method to analyze manufacturing processes in make-to-order production such as construction, shipbuilding and aviation by utilizing and extending existing process mining techniques. Among three major analysis perspectives in process mining such as process discovery, performance analysis, and conformance checking, this paper focuses on the performance analysis including workload analysis and delay analysis. To validate the proposed method, a case study with real data is conducted.

Keywords: Process mining · Manufacturing process analysis · Manufacturing execution system

1 Introduction

Manufacturing process refers to a process that is composed of sequential activities to transform raw materials into a finished product [23, 24]. To improve the quality of products and reduce production cost and time, many companies have tried to analyze complex manufacturing processes [4, 6]. Furthermore, many studies on manufacturing process analysis have been performed from several perspectives, such as process management [10], simulation [22], process modelling [7, 12], process performance analysis [8], fault detection [18], etc. Along with the methods mentioned above, process mining can be applied to analyze the manufacturing process. Process mining attempts to extract meaningful process-related information from event logs [13, 20, 21]. Manufacturing process analysis using process mining is used to understand current manufacturing processes by deriving process models, organizational models, social networks, etc. [14].

In this paper, we propose a way to analyze manufacturing processes in make-to-order industries. We investigate the characteristics of event logs in make-to-order

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production and propose a method to analyze manufacturing processes in make-to-order production, such as construction, shipbuilding, and aviation by utilizing and extending existing process mining techniques. Major characteristics of make-to-order production are the existence of a plan of the manufacturing processes, several parallel activities, and different levels of process granularity. By investigating the characteristics, several issues in make-to-order production analysis are provided; these are performance analysis considering plans, conformance checking considering activity relations, frequency, resource, processing time and detailed parallel rules, process discovery that synthesizes cases of different levels, etc. Among these issues, we propose a way to analyze the performance of processes for make-to-order production in this paper. As a method for performance analysis, workload analysis and delay analysis using event logs are suggested. To validate the proposed method, a case study with real data is conducted.

The paper is organized as follows. Section 2 explains related work, including process mining and applications of process mining in the manufacturing industries. We present characteristics of make-to-order production processes in Sect. 3. In Sect. 4, we propose workload analysis and delay analysis. Section 5 conducts a case study to validate the proposed method and Sect. 6 concludes the paper with future work.

2 Related Work

The purpose of process mining is to discover, monitor, and improve actual processes from event logs recorded by Process-aware Information Systems (PAISs) such as enterprise resource planning (ERP), workflow management (WFM), customer relationship management (CRM), supply chain management (SCM), and product data management (PDM) systems [13, 20, 21]. Event logs are recorded by events in a consecutive order, and each event has an activity related to a case. In addition, the event can have a timestamp and resource [21]. Process mining is composed of discovery, conformance checking, and enhancement. Discovery is to derive models from event logs. The alpha algorithm, heuristic mining, fuzzy mining, etc. are examples of discovery techniques. Conformance checking is to compare a given model with corresponding event logs, and enhancement is to extend or improve a model using observed behaviors [16, 19]. Likewise, process mining has many techniques applicable for analyzing processes. Therefore, process mining has been applied in many domains, such as healthcare, service, logistics, public administration, manufacturing, and so forth. For example, Mans et al. provided insights for hospital processes by applying various process mining techniques in a control-flow perspective, organizational perspective, and performance perspective [11]. Weerdt et al. proposed a framework for actual process analysis in a multifaceted financial service industry using process mining [3]. In addition, van der Aalst et al. applied process mining to the Dutch National Public Works Department managing roads and bridges to analyze invoice processes [21], Bozkaya et al. suggested a methodology for process diagnostic based on process mining and applied it to processes of government agencies [2], and Jeon et al. proposed a conceptual framework for identifying causes of inefficiency in port logistics using process mining [9].

There have been few studies in the manufacturing industries, except for Rozinat et al. who studied the applicability of process mining in ASML, a leading wafer scanner manufacturing company, and provided proposals for improvement [13]. In addition to a shortage of application cases, previous studies are difficult to apply to the make-to-order industries owing to the characteristics of their processes. Thus, this paper proposes a method of manufacturing process analysis applying process mining considering the major characteristics of the processes.

3 Characteristics of Make-to-Order Manufacturing Processes

In this section, the characteristics of make-to-order manufacturing processes are discussed. First, there exists a detailed plan for manufacturing processes. In the case of the make-to-order manufacturing industry, it is very important strictly to follow optimized and planned processes, because meeting a deadline for the clients' orders is considered as the top priority [12]. Therefore, manufacturing process analysis needs to compare a plan and an actual production (e.g., how much the actual process is being conducted as planned). Moreover, it is important to compare resources and processing time as well as the order of activities between the plan and the result.

Another characteristic of make-to-order manufacturing processes is that the manufacturing processes have several parallel activities. Because the size of the products in the make-to-order manufacturing industry is usually large, several activities happen simultaneously. Furthermore, they sometimes strictly define the relationship between event types, such as start and end between the parallel activities. For example, if there are two activities in parallel, a rule can be that an activity must start before the other starts and both activities have to end at the same time. Another rule can be that both activities have to start simultaneously and an activity must end before the other ends.

The third characteristic is that manufacturing process models usually have different levels of granularity [5]. In other words, an overall manufacturing process consists of many different subprocesses. For example, in a project for an offshore plant production, an offshore plant consists of some modules and each module consists of a number of blocks. For each block, there is a corresponding manufacturing process that is composed of various activities. These blocks build up to become a finished module. The modules also have their individual manufacturing processes for completion after combining blocks. Because the overall process has an intricate network among subprocesses and unit activities, finding a proper case is difficult in applying process mining.

In this paper, we propose a method to analyze performance of make-to-order manufacturing processes. Considering one of the major characteristics mentioned above, a different performance analysis from the traditional analysis is required. The existing performance analysis in manufacturing processes has been measuring only the results of the actual processes being conducted to compare with the criteria the business sets as its goal [10]. Nonetheless, in the case of make-to-order manufacturing industries, there are not only the actual manufacturing processes but the planned manufacturing processes. Thus, it is required to conduct manufacturing process analysis on both the actual and planned processes to identify how well the actual processes are being executed as planned. The planned processes are optimized considering the costs, efforts, and time. This is why the more the actual processes conform to the planned processes, the better the result becomes. Hence, our research tries to determine indicators to measure quantitatively the performance based on the comparison of how the actual processes deviate from the planned processes.

4 Analysis for Measuring Performance on Manufacturing Processes

In order to conduct performance analysis of manufacturing processes, we first define an event and an event log. As noted in Sect. 3, the structure of event logs for make-to-order processes is different in that it includes attributes of result as well as plan. An event and an event log are defined as follows.

Definition 1. (Event of manufacturing processes) Let A be a set of activities (e.g., tasks), R_{plan} and R_{res} be a set of resources (e.g., departments or workers) for plan and result, ST_{plan} and ST_{res} be a set of start timestamps for plan and result, CT_{plan} and CT_{res} be a set of complete timestamps for plan and result respectively. $E = A \times R_{plan} \times R_{res} \times ST_{plan} \times ST_{res} \times CT_{plan} \times CT_{res}$ is a set of events and π_n is the value of attribute n for an event $e = \{a, rp, rr, stp, str, ctp, ctr\}$.

Definition 2. (Event log of manufacturing processes) Let C be a set of events corresponding each case. $L \in \mathcal{B}(C)$ is an event log and $\mathcal{B}(C)$ means all bags over C.

Table 1. An example of events for manufacturing processes

CaseID	EventID	A	Rplan	Rres	STplan	CTplan	STres	CTres
BlockA	01	Act_1	R_a	R_a	2015-01-25	2015-03-01	2015-01-26	2015-03-01
	02	Act_2	R_b	R_b	2015-02-04	2015-02-15	2015-02-04	2015-02-14
BlockB	03	Act_1	R_a	R_a	2015-02-06	2015-02-14	2015-02-06	2015-02-15
	04	Act_2	R_b	R_b	2015-02-27	2015-02-27	2015-02-27	–
	05	Act_3	R_c	R_d	2015-03-26	2015-04-20	–	–

Table 1 shows an example of events. From the table, there are five events (E = {01, 02, 03, 04, 05}). There are three activities (A = {Act_1, Act_2, Act_3}) and four resources (R = {R_a, R_b, R_c, R_d}). Start timestamps for plan and result (ST_{plan} = {2015-01-25, 2015-02-04, 2015-02-06, 2015-02-27, 2015-03-26}, ST_{res} = {2015-01-26, 2015-02-04, 2015-02-06, 2015-02-27}) and complete timestamps for plan and result (CT_{plan} = {2015-03-01, 2015-02-15, 2015-02-14, 2015-02-27, 2015-04-20}, CT_{res} = {2015-03-01, 2015-02-14, 2015-02-15}) are also shown in the table.

We conduct workload analysis and delay analysis as performance analysis. Workload analysis aims to find the degree of workload on resources by measuring and analyzing the number of activities for the planned and the result using event logs. Delay analysis attempts to understand the degree of delay on activities or resources.

4.1 Workload Analysis

Workload analysis measures the number of activities performed by each resource in a certain period. Workload analysis shows the number of started activities, completed activities, and activities in progress. Using activity frequencies, workload analysis provides information on how much the workload of each resource is. It gives insights on how to control the manufacturing processes based on the number of activities in progress. The definitions of the number of start activities, end activities, and activities in progress in a unit period are as follows.

Definition 3. (The number of activities ()) For e = $(e_0, e_1, e_2, \ldots) \in L$, $a_j \in A$, $rp_k \in R_{plan}$, $rr_l \in R_{res}$, $stp_m \in ST_{plan}$, $str_n \in ST_{res}$, $ctp_o \in CT_{plan}$ *and* $ctr_p \in CT_{res}$, the number of activities:

- The number of started activities for plan (a_j, rp_k, stp_m)

$$= \sum_{0 \leq e < |L|} \sum_{0 \leq i < |e|} \begin{cases} 1 & \begin{matrix} \text{if } \pi_a(e_i) = a_j \\ \bigwedge \pi_{rp}(e_i) = rp_k \\ \bigwedge \pi_{stp}(e_i) = stp_m \end{matrix} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

- The number of completed activities for plan (a_j, rp_k, ctp_o)

$$= \sum_{0 \leq e < |L|} \sum_{0 \leq i < |e|} \begin{cases} 1 & \begin{matrix} \text{if } \pi_a(e_i) = a_j \\ \bigwedge \pi_{rp}(e_i) = rp_k \\ \bigwedge \pi_{ctp}(e_i) = ctp_o \end{matrix} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

- The number of started activities for result (a_j, rr_l, str_n)

$$= \sum_{0 \leq e < |L|} \sum_{0 \leq i < |e|} \begin{cases} 1 & \begin{matrix} \text{if } \pi_a(e_i) = a_j \\ \bigwedge \pi_{rr}(e_i) = rp_k \\ \bigwedge \pi_{str}(e_i) = stp_n \end{matrix} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

- The number of completed activities for result (a_j, rr_l, ctr_p)

$$= \sum_{0 \le \mathrm{e} < |L|} \sum_{0 \le \mathrm{i} < |e|} \begin{cases} 1 & \begin{array}{c} \text{if } \pi_{\mathrm{a}}(\mathrm{e_i}) = \mathrm{a_j} \\ \bigwedge \pi_{\mathrm{rr}}(\mathrm{e_i}) = \mathrm{rp_k} \\ \bigwedge \pi_{\mathrm{ctr}}(\mathrm{e_i}) = \mathrm{ctp_p} \end{array} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

- The number of activities in progress for plan $(a_j, rp_k, stp_m, ctp_o)$

$$\begin{aligned} = & \sum_{\mathrm{Min}(a_j, rp_k) \le t_l} \text{The number of started activities for plan } (a_j, rp_k, stp_m) \\ & - \sum_{\mathrm{Min}(a_j, rp_k) \le t_l} \text{The number of completed activities for plan } (a_j, rp_k, ctp_o) \end{aligned} \tag{5}$$

where $\mathrm{Min}(a_j, rp_k) = \min(\forall \pi_t \{e_i | \pi_a(e_i) = a_j \wedge \pi_{rp}(e_i) = rp_k).$

- The number of activities in progress for result $(a_j, rr_l, str_n, ctr_p)$

$$\begin{aligned} = & \sum_{\mathrm{Min}(a_j, rr_i) \le t_l} \text{The number of started activities for result } (a_j, rr_l, str_o) \\ & - \sum_{\mathrm{Min}(a_j, rr_l) \le t_l} \text{The number of completed activities for result } (a_j, rr_l, ctr_p) \end{aligned} \tag{6}$$

where $\mathrm{Min}(a_j, rr_l) = \min(\forall \pi_t \{e_i | \pi_a(e_i) = a_j \wedge \pi_{rr}(e_i) = rr_l).$

The visualization based on workload analysis is shown in Fig. 1. The figure shows the number of started activities, completed activities, and activities in progress. The blue line represents the number of started activities. The green line and the red line represent the number of completed activities and activities in progress, respectively. The red line shows that the number of started activities steadily rose until early June, then decreased afterwards.

The workload analysis can be performed according to each resource or each activity. In the case of workload analysis based on resources, it is possible to analyze the number of activities of a particular resource in a certain period. The workload analysis helps to find where the overload points are and which resource has piled the activities in progress. Likewise, in the case of workload analysis based on activities, it provides information on how much of the workload is assigned to a particular activity.

Comparison for workload analysis between the planned and the actual proceeds as follows. First, workload analysis of the planned and the actual are performed individually. Based on the results, we calculate the statistical measures for the activities in progress and then compare them. The statistical measures include average, median, maximum, and minimum values. If the measures of the actual are higher than the planned values, we need to compare the values of the started and completed activities as well. Through this comparison, we can detect problems such as where the activities

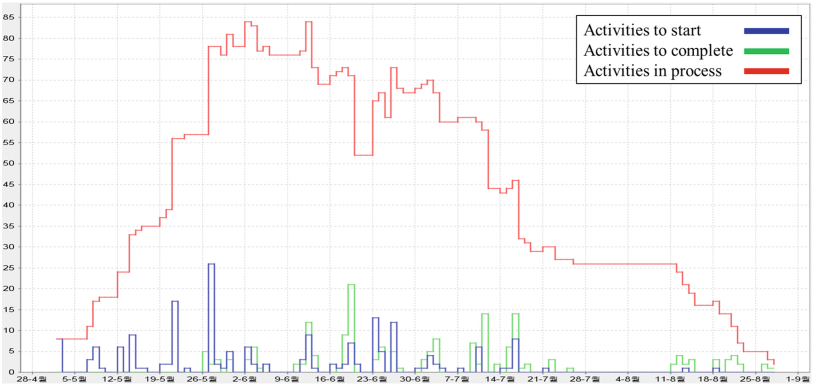


Fig. 1. An example of workload analysis (Color figure online)

are being overloaded and where the activities are not being completed in time. In addition, it is possible to understand the current state of the manufacturing processes and the diagnosis of problems through the workload analysis.

4.2 Delay Analysis

In make-to-order industries, delay is one of the factors causing the most common cost problems [1]. Delay analysis is performed to identify delayed activities and resources causing delays and to calculate the extent of delays. We define two measures, such as the delay based on completion date of an activity and the delay based on processing time. The delay is usually defined as an activity being completed later than the planned completion date [17]. Definition 4 shows the delay based on completion date.

Definition 4. (Completion date-based Delay$_{\text{time}}$ ()) For $a_q \in$ A and e = (e$_0$, e$_1$, e$_2$, …)∈L, compeletion date-based Delay$_{\text{time}}$:

$$Completion\ date - based\ Delay_{time}\left(e_i, a_q\right) = \pi_{ctr}(e_i) - \pi_{ctp}(e_i)$$
$$where\ \pi_{ctr}(e_i) \neq null \wedge \pi_a(e_i) = a_q$$

The calculation of the delay based on the completion date is useful when meeting deadline is the most important. However, it does not provide sufficient information, because the delay on completion date might be caused by a late start. That is, if a preceding activity is delayed, then following activities seem to be delayed though processing times of activities are not delayed at all. Therefore, the delay based on the processing time has to be measured as the second method. The calculation is measured by how long the actual processing time of an activity is compared with the planned time.

Definition 5. (Processing time-based $\text{Delay}_{\text{time}}$ ()) For e_i = (e_0, e_1, e_2,…)∈L and $a_q \in A$, processing time-based $\text{Delay}_{\text{time}}$:

$$Processing\ time - based\ Delay_{time}(e_i, a_q)$$

$$= (\pi_{ctr}(e_i) - \pi_{str}(e_i)) - (\pi_{ctp}(e_i) - \pi_{stp}(e_i))where\ \pi_{ctr}(e_i) \neq null \wedge \pi_a(e_i) = a_q$$

In conducting delay analysis, we first calculate the delays based on completion date and processing time. Then, we set the criteria for dividing the extent of the delays from discussion with the domain experts. Based on the results, we derive the ratios for each groups that is divided by the criteria. By doing so, activities that are frequently delayed can be detected. Likewise, it is possible to conduct the delay analysis from the resource perspective as well.

5 Case Study

In this section, we discuss a case study performed to validate the proposed method. The event logs are the offshore plant manufacturing process provided by Hyundai Heavy Industries Co., one of the major shipbuilding companies in the world. The case study is subdivided into data preparation, analysis, and discussion steps. In the data preparation, we collected the event logs from the company and performed the data preprocessing. Next, in the analysis, the performance analysis was conducted. Finally, the overall results are discussed, including comments from the domain experts in the discussion part.

5.1 Data Preparation

The event logs were collected from the information system in the company. This contains event logs for four ongoing projects. The attributes of the collected data are ProjectID, ModuleID, BlockID, ActivityCode, ActivityName, planned started and completed dates, actual started and completed dates, DepartmentCode, and DepartmentName. Among the attributes, we used BlockID as a case, ActivityCode as an activity, and DepartmentCode as a resource. The started and completed dates for plan and started and completed dates for result are utilized as timestamps.

Data preprocessing was performed because the raw data are incomplete, inconsistent, and contain noise. In the data preprocessing, data cleansing, data transformation, and data conversion were conducted. Figure 2 shows the overall events of the logs using a dotted chart [15]. In the chart, we recognized events that have null in the resource attribute and filled in the proper values using the existing information.

Furthermore, we found that a start date of an activity was incorrect. Thus, data cleansing was done by domain experts. Finally, the data were converted into data types suitable for process mining (i.e., MXML, XES). As the result of the data preprocessing, the event logs were generated as follows: approximately 700 blocks, 1400 activities, 200 activity types, and 12 departments.

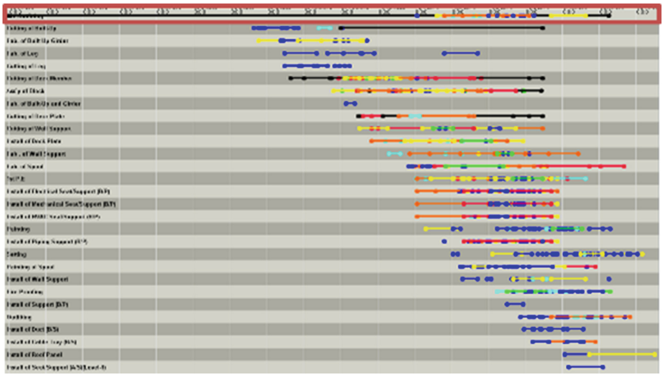


Fig. 2. An example of dotted chart results

5.2 Workload Analysis

We conducted workload analysis to understand the degree of workload of each department and each activity using the event logs.

Figure 3 is a result of the workload analysis on Department_a. The upper graph in Fig. 3 visualizes the workload analysis result for the planned and the graph below is for the actual. According to the planned, there are 21 concurrent activities on average. However, the actual number of on-going activities is 39 on average. Furthermore, in the case of the maximum number of activities, it is 64 on the planned while the actual is 95.

Fig. 3. Workload analysis results: department a

This shows that there were more concurrent on-going activities in practice than as planned. A problem regarding the overload can be found through additional comparison between the number of started and completed activities. The problem was caused by the completed activities that did not terminate in time as the planned. This led to an increase in the number of on-going activities. Even though the department started the activities 40 days earlier than they were planned, the activities were delayed and completed 20 days later. Figure 4 shows the workload analysis on the activities performed by Department_a. Among the five activities, Activity 2, Activity 3, and Activity 5 have the same problem shown in Fig. 3.

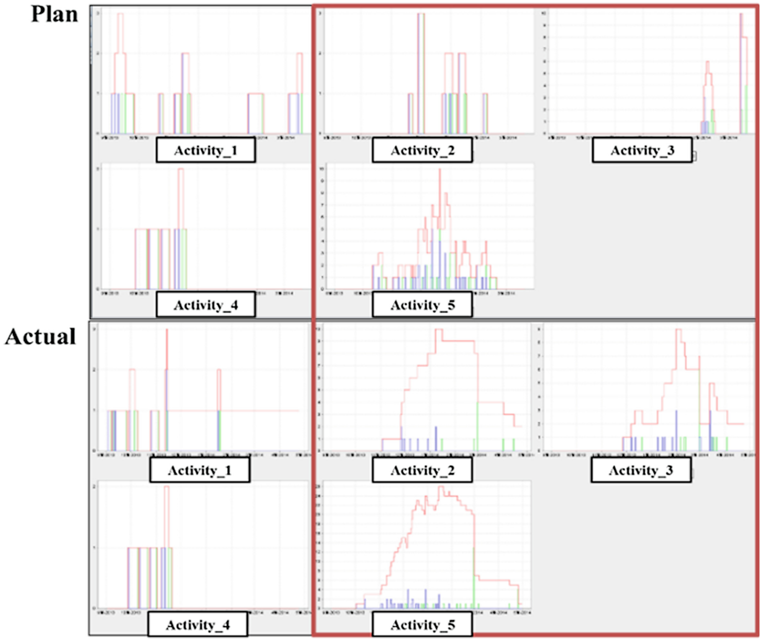
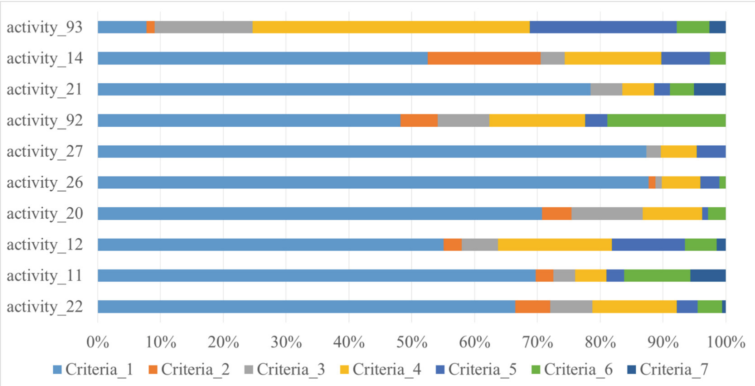


Fig. 4. Workload analysis results: activities of department a

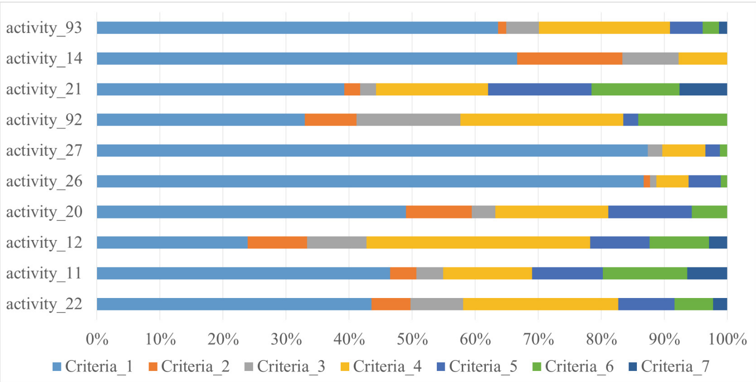
5.3 Delay Analysis

We performed the delay analysis to determine the degree of the delays on each activity and each department using event logs. There are two criteria when measuring the delays, completion date-based and processing time-based. As shown in Fig. 5, the delay analysis was carried out for the top 10 most frequent activities out of 200.

Seven criteria were defined considering the extent of the delays. For instance, in Fig. 5(a), activities with no delay were classified into Criterion 1. Activities with less than five days of delay were classified into Criterion 2. Similarly, we classified activities with less than 10 days of delay into Criterion 3, less than 40 days of delay into Criterion 4, less than 50 days of delay into Criterion 5, less than 100 days of delay into Criterion 6, and 100 days and more of delay into Criterion 7. In the same way, we classified each activity by the processing time in Fig. 5(b). Afterwards, we calculated the frequency ratios for each criterion and visualized them in Fig. 5. In Fig. 5(a), we can identify that Activity_26 and Activity_27 were performed 90 % of the time with no delay. In contrast, Activity_93 and Activity_92 were mostly delayed. To understand the number of delays based on processing time, Fig. 5(b) is shown. Activity_93, which was delayed over 90 % of the time in Fig. 5(a), was completed 65 % without any delay in Fig. 5(b). The main reason why Activity_93 was more delayed in the completion date-based scheme rather than the processing time-based scheme is the actual started date itself was delayed from the planned date.



(a) Completion date based



(b) Processing time-based

Fig. 5. Delay analysis results: Activity perspective

5.4 Discussion

The previous section showed that performance analysis including workload analysis and delay analysis can be applied to real data. To evaluate the suggested method, we had several meetings with domain experts. Through the discussions, we obtained feedback on the results as follows.

A department located outside the factory can cause delays or overloads. In the results of workload analysis and delay analysis, Department_a had problems. According to the results of workload analysis, there were more activities in progress in actual processes than in planned processes in Department_a. In addition, we found that approximately 60 % of activities performed by Department_a were delayed from the results of processing time-based delay analysis. Through the discussion, we discovered that Department_a was located outside the factory, which makes it difficult to control and manage compared with other departments.

In addition, we found that some reworked activities were delayed. If a product with defects is found, reworks of activities are unavoidable to repair it. Once an activity is reworked, it typically takes a few more weeks compared with the planned, thus reworked activities may cause delays. For example, in the case of painting activities, they had been delayed by frequent reworks because the activities have a high failure rate.

Besides, there were other factors to bring about delays and overloads. Activities performed in the rainy season were more frequently delayed than activities in other seasons. About 37 % of delayed activities were performed in June to July, when the rainy season starts in Korea. In addition, improper planning of activities may cause overloads because low-priority activities would be delayed to deal with unexpected conditions. For example, if the number of resources is significantly changed from the plan or if raw materials do not arrive in time, the activity would not be completed at the planned date and the number of activities in progress would pile up.

We introduced performance analyses to determine which activities or departments have problems based on the results. Our study has an advantage in understanding the current situation by comparing the actual processes with the planned processes. On the other hand, it is difficult to identify exact causes of problems through the results. This limitation can be overcome by discussion with domain experts, as presented above. In addition, although most of the other analyses have the same issue, the results of the suggested performance analyses are highly dependent on the quality of data because event logs used in this research consist of planned data and actual data. For that reason, this study needs well-structured data from MES to obtain meaningful information from the obtained results.

6 Conclusion

This paper provided characteristics of manufacturing processes in make-to-order production and proposed a method for performance analysis including workload analysis and delay analysis. Workload analysis, which analyzes the degree of workload, and delay analysis, which examines the degree of delay in the activity and the resource perspectives, were proposed. In addition, a case study was conducted to validate the proposed method. In the case study, we were able to understand the current situation and detect the causes of the problems by comparing the planned with the actual processes. As future work, we plan to analyze a method to make a plan for precisely processing time of activities considering the level of difficulty of an activity measured by the results of performance analysis. At present, it is difficult to predict the processing time of each activity because even if the activities are the same, the processing time of an activity varies according to the level of difficulty. Therefore, reflecting the level of difficulty in conducting activities can be a solution to design a proper plan. In addition, we intend to develop an indicator that provides the degree of how much actual processes deviate from planned processes. Although conformance checking detects and quantifies inconsistency between event logs and models, it needs to be extended to deal with the manufacturing processes in make-to-order production. After discussion with the domain experts, we determined that not only activity relation and frequency but also resource, processing time, and detailed parallel relations should be considered when analyzing the conformance checking. Hence, we propose to study comprehensive conformance checking analysis for manufacturing processes in make-to-order industries using process mining.

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