Using Process Mining Approach for Machining Operations

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2 authors:

Zeynep Altan
Beykent University

Semra Birgün
Doğuş Üniversitesi

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Zeynep Altan[1(✉)] and Semra Birgün[2]

[1] Software Engineering Department, Beykent University, Istanbul, Turkey
zeynepaltan@beykent.edu.tr
[2] Industrial and Systems Engineering Department, Fenerbahçe University, Istanbul, Turkey
semra.birgun@fbu.edu.tr

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Abstract. In the Industry 4.0 world, both service and manufacturing companies should review their systems and processes, remove any application that causes waste, ensure lean flow and change business models if necessary, in order to fulfill the requirements of this trend. Introducing Industry 4.0 on a problematic system or process might harm it enough to cause the company disappear instead of benefiting it. For applications correctly decided to be built upon a correct system, data flow must be accurate and timely. And at this stage, data amount that increases with process mining and complexity of the big data will be solved and more information will be obtained about real production processes and data. In this study, a prototype is developed using the data of a previously studied manufacturing research. This prototype handles only one phase of the manufacturing process and extracts all the initial possible pathways of this phase through process mining.

Keywords: Batch production · Event logs · Manufacturing process analysis · Process improvement · Process mining

1 Introduction

The documentations of the processes are substantial for many developers while developing any product in the discipline of software engineering. Even though the working software instead of documentation is determined as the second rule of agile manifesto [1], today's software sector demands the documentation in solving complex problems [2]. Logs that are kept in the development stages of any product are a part of the management system and they also explain the roles of developers in the process. Logs about different activities carried out in the process in classic systems are not included. Systems developed over time have started to feature the activity models in the processes [3]. This architectural model has entered the world of software as Model Driven Software Engineering. From here, the transition to process models in which activity logs in the management system documentation processes took place.

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Process mining is a discipline in which business processes based on event logs are analyzed. The discipline has made a non-erasable entrance to the sector with a manifesto. Process mining manifesto was written by members and supporters of IEEE Task Force [4]. Its objective is the discovery, control and development of real processes from easily accessible logs from the current information systems. According to the manifesto, detailed information can be obtained from data sets with process mining methods and development of processes can be supported in such an ever-changing competitive business environment.

In process modeling, instead of assumed process values, recorded real event logs and performance related and compliance related analysis are made. The purposes of analyses may vary according to the business processes. Business processes can be generalized as manufacturing, distribution, logistics, supply chain, accounts payable, service management - IT etc. The purpose of the analysis, in other words the methods in this context may be the comparison of the process realized to the target process. Another main purpose of analysis with process mining methods can be to observe the current situation before deciding on the design of a new application. This requires the analysis and understanding of the current structure. Determining the most common paths and main insights about the process will illuminate the decision makers. Big projects that extract knowledge from event logs and their development tools [5] are partners of international organizations on works about various industrial subjects [6].

In his study, Van der Aalst [7] explained the modeling of processes in detail by using event data. Here, the relations between logs and models they use are explained with conceptualizations and visualizations. Van der Aalst's classification as log abstraction and model abstraction targets combining different types of behavior of processes instead of examining the different techniques of the processes. In the study, Petri Nets [8] and Structured Process Models [9] from activity sets are given as examples of different process models.

Suriadi et al. [10] carried out a study on the process behavior of a big insurance company and in this case study, they employed the life circle of process mining model developed by Van der Aalst called planning, extraction, analysis, interpret, improvement. Techniques used for data analysis transforms the problem that will be modeled in a complex structure into a simple process model that is easy to read.

Varbeek et al. [11] worked on process discovery, process conformance and process improvement in order to develop a tool named Divide and Conquer. As applications containing many activities are worked with, process mining approach is generally automated.

Lu et al. [12] refine the event logs and found and removed the tasks to be duplicated in determining the related processes. The study was then applied in the hospital project. Knoll, Reinhart and Prüglmeier [13], Son et al. [14], Sani, Zelst and Van der Aalst [15], Turner et al. [16], Tax, Genga and Zannone [17] and Gupta [18] are some of the authors that work in the process mining field.

In the next parts of the study, after giving a brief information about the methodology aiming at the effective application of process mining to different projects, an earlier research done on manufacturing sector has been restructured using its data.

2 Applied Process Mining Methodology

There is not one single approach used in the process mining applications. However, what is aimed at the end of all different approaches is to increase the performance of the process and check the compliance of the process with the rules. One of the process mining approaches in project management is the examination in three steps of initialization, analysis and iterations and improvement [19]. The purpose of this methodology called Process Mining Project Management - PM2 is to make sure the processes of the systems developed are in compliance with each other. Thus, the performance of the system processes will increase. Applications in which this approach is used can be both purpose related problems and data related problems. Life Circle of Process Mining Projects (PMPL) [20] is the development of product as iterative in the scale of processes of the life circle.

In the PM2 methodology, the data in the processes of the current situation in the analysis phase are used. For example, the conformance of these processes to the ideal behavior can be checked or done discovery analysis or done performance analysis can be carried out. The results of these analyses will naturally ensure the improvement of the process. The second important task of the approach in the planning phase is the study of the knowledge extraction stage. The most crucial part of the process mining is the determination of event data.

It is known that the analysis of the information that consists of the business processes in the process mining is different from the data mining techniques. When in fact in both approaches large data sets, i.e. big data are worked on. But in data mining, data tables and the relations between these tables are analyzed. However, in process mining, the relations among data patterns are not extracted. Instead, process relationships in the data sets are analyzed. Another important feature of process mining is that working processes eliminate the data collection condition of the existing data set. Therefore, process mining is carried out with the performance analyses of the process model that strengthens the relationship between data set and business processes.

The extraction stage of the PM2 methodology is important in process mining. Clearing of this phase is impossible by deciding the granularity of the event data. Because data set that will be compared as the event log will vary according to the characteristics of each application. The elements of the set may be quality, time, resource or cost according to the business process. Key attributes can be defined as caseID, activities and timestamps event logs. In many studies, determining event logs may be made with different techniques. For example, interview techniques such as asking questions in surveys are one of the preferred approaches in this process. Therefore, the events can be decided with the question driven approach.

The purpose of the data processing phase is to obtain different forms of current event data of event logs. In other words, as event data is used as input in the data process model, event logs are used in mining and analysis phases. Mining/analysis stage that aims to increase the performance investigates the product's verification/validation (V/V) analyses processes' improvement possibilities. PM2 methodology that consists of main phases of initialization, analysis and iterations and process improvement will be taken as the fundamental approach. In this study, a similar flow will be observed and the related extractions will be decided through planning on the initialization phase.

3 An Application from Manufacturing Industry

The study takes the Ph.D. thesis [21] that analyses the manufacturing of parts in the manufacturing industry as resource. The study referenced is completed through different processes including raw material machining, heat treatment and grinding. Only the first phase of this flow referenced as remodeling is decided to be renewed with process mining. This flow is the generalized modeling of the transfer of raw material from the storage to the heat treatment operations in different machines. That modeling is a prototype. The reason for the review of the existing project with a process mining approach is to increase the performance of related business process and check its conformance to the given rules. In this context, the business process of the study will consist of the planning phase's inputs as an as-is system. This data is the current state data during manufacturing. Due to the structure of the methodology followed, the existing state's processes are used in the analysis phase.

In this prototype study, process mining was carried out with the aim of improving the machining process of the manufacturing company mentioned above. The company operates in the automotive industry and manufactures propeller shafts, pump drive shaft, power take-off shafts and their components and spare parts. Despite 3 shifts per day, the company needs 900 min/day overtime. The examination of the past manufacturing data shows that high level of variability in demand and manufacturing time cause imbalances in production and overtime is needed in order to rush production as a result of extension of lead time. As a result of this, the transition to lean production is initialized to improve the system, planning the manufacturing processes with more realistic data is decided and process mining is employed with the aim of collecting the correct data at the correct time.

Based on the company's past demands, the manufacturing process of the propeller shaft (which is the main product) was selected as the pilot area for lean production process. Universal joint kits (UJKs) product family determined among 3 families after the cellular production studies on the process in which products are produced in discrete batches are the subject of this study. The production flow of the UJKs brought from the warehouse are carried out in three stages of machining, grinding and heat treatment and UJKs produced are assembled to propeller shafts or packaged as the spare parts kit. The description of machines used in the application about machining processes is given in Table 1.

Table 1. Machinery to be used in process

Machine ID	Machine definition
M15	Semi-automatic lathe
M50	Drilling and tapping
M51	Special milling
M52	Special milling
M58	Manual press

The raw material to be examined for its transfer from the warehouse to the heat treatment are UJKs which are always ready for use. It is accepted that there is no limit for these UJKs and they are always ready at the warehouse. The batch size is 100 units. The first raw material batch from the warehouse will enter the queue of the first machine (M15) to be processed. After machining operations finish, the batch from the last operation will be first to wait to enter the furnace. As the furnace charge is 1000 units, the furnace entrance takes place after 5 batches are completed. Accumulating of the work-in-process (WIP) in front of the furnace makes the solution of the problem complex. It will be important to reveal and display both the WIPs in front of the furnace and the empty capacity waiting and/or overloading in the stages before coming to the furnace. The fact that these analyses will be determined for each machine will make the process mining important.

Following definitions are given that were taken from the system-as-is, in other words from the current system, in order to complete the information about the event logs (Fig. 1).

(i) Six different resources, i.e. routes P05, P12, P20, P24, P31, P41 are obtained from the existent system.
(ii) The system will complete an iteration when a batch with 1000 units is processed from storage to furnace. Each batch at the beginning has 100 pieces. They enter machining one by one and are carried to the other machine after getting their operation completed. In other words, parts (in batch of 100 units) that are transmitted to enter machining in the M15 machine from the storage come with one of these batch numbers.
(iii) P05, P12, P20, P24, P31, P41 have different paths and these also demonstrate the probable routes of parts in transition from Storage to the Furnace. For example, P12, P24, P31, P05, P24 and P41 routes are individually transferred from the Storage for machining in M15 machine. The transfer time from the Storage to the first machine-M15 is neglected. Then, the related parts will follow their own routes to reach the Furnace.
(iv) The following activities will take place in each communication between machines.
    (a) Transport - T1
    (b) Processing
    (c) Transport to Furnace – T3 (This activity only takes place during the process of moving the parts to the furnace).

In this study, an existent manufacturing application [21] is restructured using Disco tool [22] handling the action times of the production at each machine. Action times are taken as event logs. The results extracted from the probable event time of the current model are analyzed. Resource annotations are given about the expression used by Disco in Table 2. Resources are the all probable paths from the beginning (Storage) to the target (Furnace). The flow of the routes (resources as used in Disco) can be followed from Fig. 1. Each route on manufacturing processes include all processing flows of different UJKs:

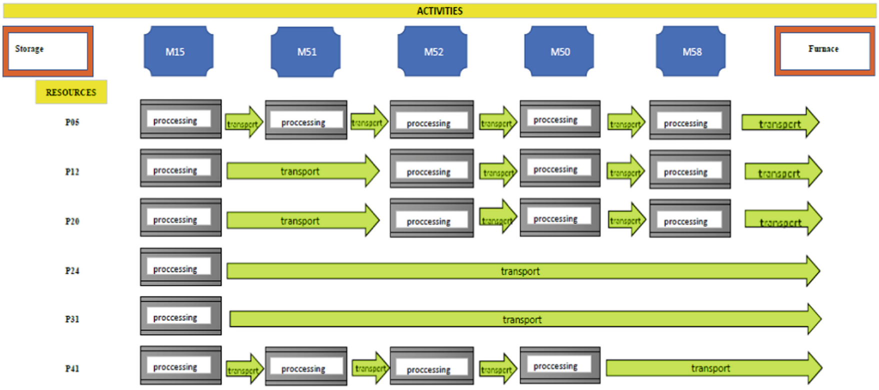


Fig. 1. Flow of resources from storage to furnace for each batch

i. 50% of the UJKs that completed their turning operations in M15 machine are directly sent to heat treatment and accumulated before heat treatment.
ii. 20% of the UJKs that are turned from the M15 machine are sent to the M51 special milling machine queue.
iii. Parts machined in M51 machine enter the queue of M52 machine which is the special milling machine.
iv. Also 30% of the turned UJKs from M15 machine enter the M52 queue.
v. Transactions in the queue which consist of 50% of the total are rotated to the M50 drilling and tapping queue.
vi. Machining activity is carried out in M50.
vii. 25% of the UJKs from the M50 machine are sent to the M58 manual press and 75% are sent to the heat treatment queue.
viii. UJKs pressed on the M58 machine are sent to the heat treatment queue.

Table 2. Case IDs and their UJKs corresponding to resources for the first iteration

Resources	Case IDs	UJK (100 Cluster)
P05	000-006	1 2
P12	002-003-008	1 2 3
P20	013-014-009	2 1 3
P24	004-005-010-011-012	2 3 4 1 5
P31	015-016-017-018-019	3 2 1 4 5
P41	001-007	1 2

The probable distributions of different routes are explained as Case IDs. 20 different caseIDs are specified changing according to various UJKs. More clearly, with the processing of the existing data values, the number of probable different cases where the 1000 pieces initiated to be processed in batches of 100 in the M15 machine were obtained as 20. For example, for the P24 route 200 items are processes by caseID 004, 300 items are processed by caseID 005, 400 items are processes by caseID 010, 100 items are processes by Case ID 011 and 500 items are processes by case ID 012. P31 route complements the different items corresponding to caseIDs of P24 route. Each paths of P3 and P24 routes include 500 items in total. In this sequence, caseID 012 in P24 route and caseID 019 in P31 route are processed independently.

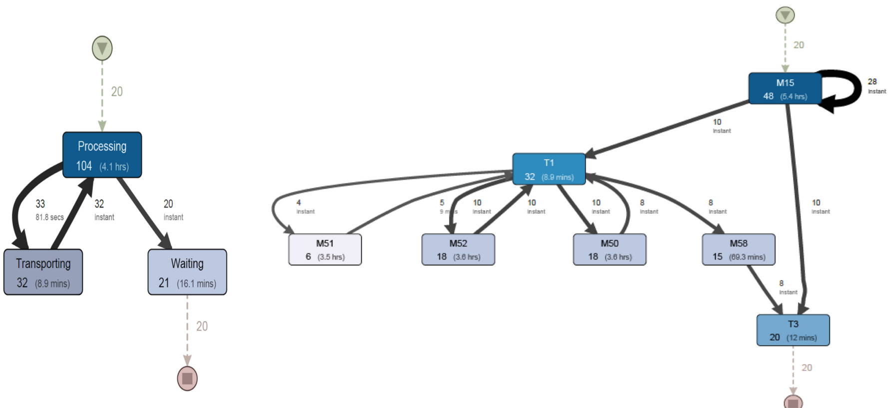
As explained in the previous section, the system in which process mining will take place will use the real data of the current system. Since the event logs are determined by the average processing times of the current study, there is no need to utilize any approach of PM2 methodology to determine the event logs as the initialization step. Table 3 is organized from the existing study to include average process times of machines of per item for different routes. Event logs for each route are obtained by processing these average times from an accepted start time. Processing time (mins/unit) has been distributed randomly for each route in each machine.

Table 3. Processing times for each resource (route)

Route	Mach.	Processing times (min/unit)														
P05	M15	5,17	1,67	0,95	2,37	**2,10**	1,59	4,05	3,16	3,00	2,56	1,69	4,29	0,95	2,58	4,5
P12		1,76	**2,27**	2,77	2,32	2,16	1,71	2,22	1,84	1,74	4,24	2,03	1,76	2,76	3,0	2,84
P20		1,48	2,3	2,44	1,69	3,99	**0,87**	2,20	2,76	2,7	3,91	0,92	2,16	3,91	1,48	2,3
P24		1,71	2,35	2,57	2,85	2,61	0,84	1,76	4,89	1,79	2,26	3,18	2,35	2,4	2,43	3,02
P31		1,81	0,89	4,17	0,85	2,22	4,84	2,20	2,39	2,65	2,92	4,09	1,69	2,21	1,79	1,77
P41		2,61	2,7	2,57	3,21	3,88										
P05	M50	1,55	1,48	1,88	1,71	1,80	1,50	2,0	2,25	1,50	1,86	1,43	1,64	1,50	1,68	1,42
P12		1,48	2,19	1,73	2,75	1,59	1,81	2,89	1,61	2,4	1,78	1,55	1,94	1,50	1,61	1,33
P20		1,68	1,67	1,6	1,67	1,92	1,35	1,80	1,72	1,62	1,42	1,70	2,22	2,25	1,64	1,68
P41		1,96	1,51	1,69	1,50	1,96	1,93	1,62	1,58	2,3	1,70					
P05	M51	2,75	1,42	1,5	1,59	1,68	1,58	1,68	2,25	1,74	1,9	2,7	1,5	1,5	1,7	2,0
P41		1,87	1,96	2,25	2,22	1,59	1,78	2,73	3,75	3,22	1,96	1,87	1,6	1,61	2,4	1,81
		3,4	2,3	2,3	1,93	1,95	1,81	1,62								
P05	M52	1,35	2,65	2,79	1,8	1,5	1,58	2,25	1,96	1,67	1,54	1,8	1,5	1,46	1,5	1,81
P12		2,3	1,61	1,67	1,54	1,18	1,98	1,42	1,59	1,86	1,93	2,4	1,67	1,42	1,5	1,72
P20		1,33	1,73	1,68	1,62	1,96	1,73	1,67	1,67	1,61	2,75	1,68	1,96	1,6	1,81	2,19
P41		1,35	1,55	2,20	1,5	2,0	2,25	1,59	1,61	1,8						
P05	M58	0,5	0,9	0,7	0,6	0,41	0,36	0,66	0,72	0,8	0,55	1,2	0,49	0,35	0,39	0,48
P12		0,32	0,67	0,53	0,38	0,59	0,58	0,33	0,21	0,4	0,64	0,21	0,98	0,96	0,8	0,42
P20		1,17														

The analysis results and performance evaluations of the model from the Storage to the Furnace for all possible events were obtained by using Disco tool. Visual solution of the processed data can be seen in Fig. 2. Figure 2-a shows the result of the three entities (processing, transporting and waiting), which are defined as activities according to absolute frequencies and mean processing times. Moreover, frequency values between the entities are also given. In Fig. 2b, the information taken from each machine and their entities are analyzed separately. It is also possible to obtain total, maximum and minimum duration times for each action and machine. These values will help to decide the best probable route after many iterations.

Table 4 and Fig. 3 gives detailed information about the statistics. Table 4 summarizes the results of Disco. An attribute called variant has been automatically created in Disco. This attribute shows how many actions are completed in each event. For example, Disco groups the case 010 and the case 018 with variant number 5. Variant 5 shows that the routes include 5 events from the Storage to the Furnace. While probable path P24 with case 010 continues 1 day 8 h, the other probable path P31 lasts 20 h 27 min with case 018. The similarity of both route is that they complete their paths with 5 different events.



(a) (b)

Fig. 2. Map of the activities between absolute frequency and mean duration (A) According to total actions (B) According to machines

Activity details of two different cases (case 003 and case 014) for one iteration is presented in Fig. 3. Processing of case 003 in the machine M15 finishes at 10.27 and the processing of case 014 starts 10.27 in the same machine. Because the route P12 and the route P20 complements each other as 300 items. Since the route P12 processes 100 items, all activities in each machine will be completed with one event. For example the lead time in machine M15 continues 87 min (0,87 min per item –Table 3). On the other hand, the route P20 processes 200 items, and all activities in each machine will be completed with two consequtive events. The lead time in machine M15 continues 210 and 227 min sequentially (2,1 and 2.27 min per item –Table 3). The total lead time of M15 machine with P20 route lasts 7 h 17 min. Transporting time is accepted as 5 min for 100 items, and 10 min for 200 items totally. Since the duration times mins/unit has been taken randomly, it is precision to take more then one iterations to decide the best route to process at machine M15.

Table 4. Distribution of events in terms of cases and their treatments

Variant Number	Event Amount	Case IDs	Resources (No. of Batches)	Processing Lead Time
1	8	001 003 013	P41 P12 P20	16 HRS 24 MINS / 9 HRS 4MINS / 14 HRS 47 MINS
2	12	002 014	P12 P20	18HRS 05 MINS / 1 DAY 5 HRS
3	3	004 015	P24 P31	16HRS 17 MINS / 10HRS 26 MINS
4	4	005 016	P24 P31	1DAY 1 HR / 14HRS 44 MINS
5	5	010 018	P24 P31	1DAY 8 HRS / 20HRS 27 MINS
6	6	012 019	P24 P31	1DAY 16 HRS / 1DAY 1HR
7	2	011 017	P24 P31	7HRS 35 MINS / 5HRS 23 MINS
8	10	000	P05	13HRS 47 MINS
9	15	006	P05	20HRS 21 MINS
10	16	008	P12	1 DAY 3 HRS
11	16	009	P20	1 DAY 20 HRS

Total processing times complementing each other with different routes (P05–P41 and P24–P31) for all other case pairs can be given similar to the Fig. 3, and it is also possible for other case pairs of P12 –P20 routes. Figure 4 summarizes the all statistics of the model.

Another example is given in Table 5 for a single iteration process of the 1000 parts product in which the processes are carried out. Parties following the P12 and P20 routes account for 30% of all processing batches and are processed in the M15 machine as given in Table 5.

Since 1000 pieces were required for the furnace charge, it has been stated that the raw material output from the warehouse was accepted as 1000 pieces. In the exemplary study, the batches were treated with three different probabilities as 500, 300 or 200 parts in M15 machine with P24 and P31, P12 and P20, P05 and P41 routine couples, respectively. As the analysis results of each route pair will be discussed in the model,

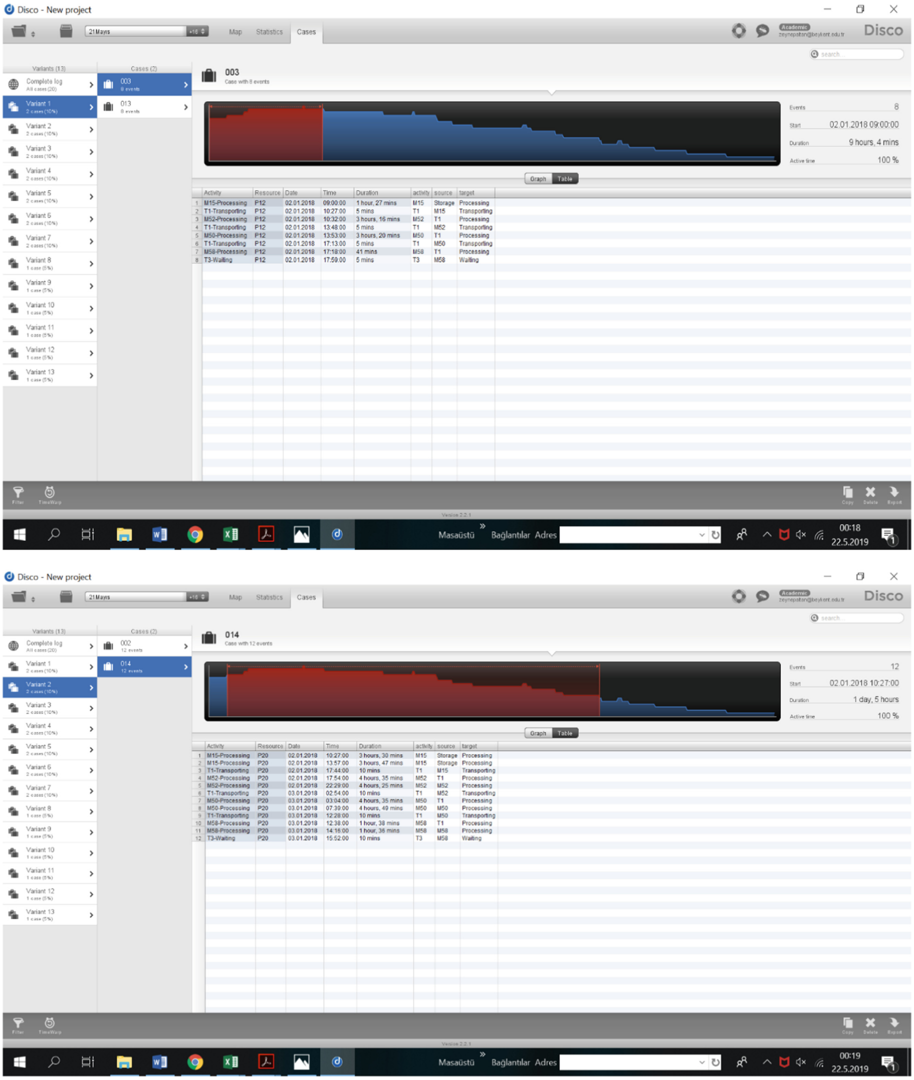


Fig. 3. Total duration times of case 003 and case 014 for the routes of P12 and P20

the start time in the M15 machine is the same (02.01.2018, at 9: 00). For example, for the P12–P20 route pair, the first operations of the M15 machine start with P12 route. P12 starts the processing with 100 items and 200 items possibilities, respectively. In this case, P20 completes the activities of processing 30% (300 items) with 200 items and 100 items, respectively. In addition, two individual activities were started to process from the start time for 300 items by P12 and P20 routes, seperately. Thus, the model created 6 different case IDs for P12–P20 pairs: case 003, case 002, case 008 for P12 route and case 14, case 013, case 009 for P20 route.

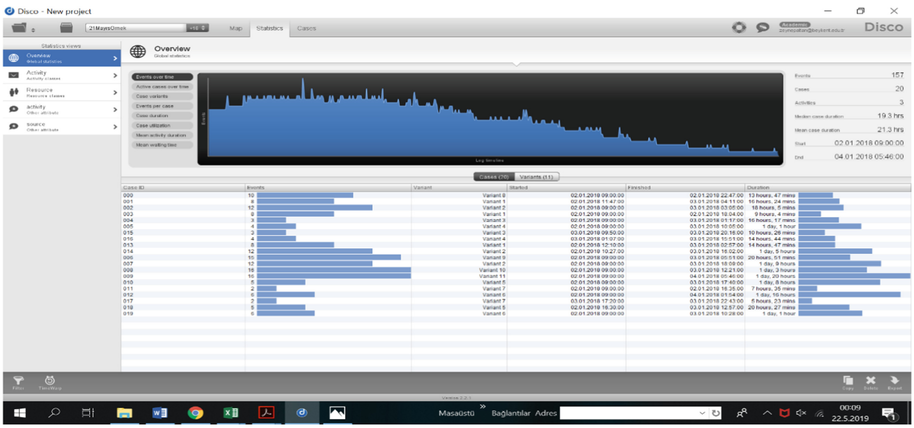


Fig. 4. Global statistics of all cases

Table 5. Results of sample cases

Case	Total lead time
2 pieces P12 (Case 002) and 1 piece P20 (Case 013)	18 h 05 min (12 events - Case 002) + 14 h 47 min (8 events - Case 013)
1 piece P12 (Case 003) and 2 pieces P20 (Case 014)	9 h 4 min (8 events - Case 003) + 1 day 5 h (12 events - Case 014)
3 pieces P12 (Case 008)	1 day 3 h (16 events)
3 pieces P20 (Case 009)	1 day 20 h (16 events)

In the continuation of the study, all party groups will be considered at the same time and the flow which gives the shortest lead time will be calculated according to the results.

4 Conclusions

Process mining projects generally aim at the improvement of processes effectively. Therefore, the target of a process minig project is to achieve the time and cost reduction and to increase the performance of the system. The methodology accomplishes these criteria by using event data. Whenever event data is obtained as event logs, process model orders the activities in a process. Tool support of process mining methodology is also important to analyze the problem interactively, and to reduce the time-consuming.

This study gives a small process mining application analyzing probable paths of a manufacturing model. Different lead times of machine loads are evaluated. The data used in the model is taken on a variety of parts of an existent manufacturing system. This is a prototype application. It is aimed to determine the possible amounts of various routes in order to decide the transition times of different batches into the oven in an optimum time. The effective use of machines will be realized by analyzing the process times after the starting time of the case pairs according to different parameters.

In the system, which deals with the processing of raw material from warehouse to machining operations and up to the heat treatment, statistical results are obtained about the combination of batches of UJKs with different batch numbers in different possibilities. In later studies, detailed analyses of this prototype and the application of it to all processes in the production of raw material.

For big projects at different sectors process mining will soon become very important since it extracts knowledge for event logs recorded by the system. Nowadays, event logs are rarely used to analyze the underlying projects. Utilizing the process mining tool, it is possible both to control business processes and to discover their performance.

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