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Abstract— **Nowadays, many companies carry out efficiency studies to increase their profitability. The most important step in productivity studies is to objectively analyze the processes and identify the points that can be improved. Process mining shows the actual functioning within the process. It also identifies points of improvement such as bottlenecks, waiting times and deviations in the process. In this article, it is aimed to analyze the production process of the barrel electrolytic coating line with the process mining method. In order to perform the analysis, firstly, the data related to the production process was obtained from the ERP system in .csv format. Within the scope of process mining, data obtained from the event log were used to analyze and visualize the processes affecting the coating line and to identify areas where improvements can be made. Process mining techniques were applied to the event log of the production identified after the electrolytic coating process. ProM 6.12, a widely used open source tool for process mining, was used to perform our analysis. After examining the in-line processes of the product produced in the electrolytic coating line, the data from the event logs were processed and analyzed with process discovery algorithms. In the literature, there has been no research to date on using a process mining perspective to detect anomalous flows in electrolytic coating production.**

Keywords— Barrel Electroplating, Process Mining, Petri Nets, Inductive mining.

I. INTRODUCTION

Industrial production systems attach importance to quality, efficiency, cost and cycle time in production in order to survive in the competition in the global market. In order to increase quality and efficiency, it is necessary to see how the production process works and to detect abnormal points that can be improved. Semi-finished products are subjected to the coating process for protecting, decorating, or improving their surface properties. We usually carry this coating process out on automatic electroplating lines. The process begins by loading the barrel onto a robot to ensure its transfer and immersion into chemical baths. Baths may contain substances such as sulfuric acid containing corrosive baths, substances such as tin and nickel containing metallic solutions, or simply rinsing water [1]. Considering the control, technological complexity and economic importance of electroplating lines, the ability to detect abnormalities in the product while the production process is ongoing and to intervene immediately plays an important role in terms of quality and efficiency.

Process mining, which is the missing link between data mining and machine learning techniques, is used to discover production process information from event logs got from industrial production systems, data flow diagrams, Petri nets, etc. It is an emerging tool used to create process models and detect abnormal events in the production system through conformance analysis. The main goal of process mining techniques is to extract a clear process model from event logs and then bridge the gap between traditionally simulated model-based process analysis and data-driven analysis techniques, such as machine learning and data mining [2]. Process mining is operational through the systematic use of event data. It aims to improve processes [3]. There are clear distinctions between process mining and data mining in processing log data. While data mining focuses on existing data for analysis, process mining focuses on the processes by which this data is created and how they are related to a process. The important differences between these two approaches arise in their analysis and process-oriented perspectives. Data mining aims to detect patterns or make predictions by examining groups of data. Process mining models data analysis to get deep insights into processes using recorded event logs [4].

Process mining explores relationships between events in the workflow, as well as Petri nets, causal networks, BPMN, etc. It uses to create visual representations of the scenario of the entire production process in terms of process flow [5]. As a type of process mining, there are discovery, adaptation and development stages [6]. Process discovery creates a process model from the event log based on the flow of control, the order of activities. Whether a process model matches the actual behavior recorded in the event log, conformance can detect deviations checking. In the development phase, it aims to develop or improve the existing process model based on the insights got from the event log [6]. In this article, we use performance analysis to model the barrel electroplating line and detect times in the process while using process discovery and compliance analysis to detect anomalies within the modeled process. The article covers pre-processing of event logs from a very complex electrolytic plating line and converting them into event logs suitable for process mining; Analyzing the created event logs with process mining, how the process model of the electrolytic coating line is created, and performing a suitability analysis of the created model to detect abnormal behavior; Process mining discovery algorithms have contributed to the literature with the success of heuristic and inductive mining algorithms in detecting abnormal behavior. We applied process mining to the data got from the electrolytic coating line of Aksan company.

II. Literature Review

Moussab et al. [2] tried to detect anomalies and deviations in the process with machine learning algorithms using data from an electroplating line. However, they were unsuccessful because they had difficulty in defining the variables of abnormal events. We could not find any other studies to detect anomalies in the electroplating line. We have carried studies out to solve line scheduling problems by modeling them with petri nets. Maeyens and his team [7] investigated the feasibility of process mining techniques for analyzing event data got from machine logs. We propose a new method based on process mining to profile abnormal machine behavior. First, we created a process model from the event logs of healthy machines. We then compared this model with the process models of other machines using the conformity check technique. Because of this comparison, we obtained a series of fitness scores related to differences in the model structure and specific processing times. The resulting suitability scores were used to identify and detect inverter outages.

Z. Tariq et al. [8] presented new compliance analysis techniques to service-oriented organizations for in-depth analysis of complex business processes. We examined individual compliance trends in process instances in the event log to detect anomalies in real-world business processes early. The compliance trend provides failure prediction as well as investigating the root causes of issues leading to business process failure. In the work of O. T. Baruwa, M. A. Piera, and A. Guasch [9], the scheduling problem of a flexible manufacturing system is planned to use timed color petri net (TCPN) modeling, where each operation has a certain number of preconditions, an estimated duration, and a set of post-conditions. Based on the accessibility analysis of TCPN modeling, we proposed a heuristic search algorithm that finds optimal or near-optimal deadlock-free schedules with generation time as the performance criterion. M. Mabed et al. [10] discussed the use of various Petri nets to model the electroplating line. These are TPN, TCPN models. They mentioned the advantages of these networks, in which Z/pZ TPN can be easily applied to industrial problems.

III. Barrel Electroplating Process Mining

Barrel coating is a method of coating small parts using a horizontal type drum (barrel) that can be operated automatically [11]. Also known as Drum Plating, the barrels rotate slowly as we soaked them in a series of cleaning, electroplating and passivation chemical solutions. We tumbled the barrel while the metal components inside were cleaned and coated when immersed in a series of chemical treatment tanks containing plating baths. Typically, these parts are relatively lightweight, small hardware that is resistant to damage and deformation [12]. Coating surfaces are used to provide (alone or in combination) the following three functions: (a) corrosion protection, (b) decoration/appearance and (c) engineering coatings (for wear surfaces or dimensional tolerances). Barrel plating is most often used for corrosion protection. Because of the surface contact inherent in the rolling motion during machining, we do not use barrels for decorative or engineering coatings [13]. Products often remain in the same barrel for further processes such as cleaning, electro cleaning, rinsing, pickling, chroming, drying, or sealing. It is important to avoid removing a barrel from the bath before it has completed its operation. It is also important not to allow the barrel to remain in the bath for more than a certain period; Otherwise, product surfaces may be damaged. Therefore, soaking times are defined by an interval for each bath.

When moving under load, a robot may not hover in the air to prevent product oxidation. Robots can only wait when they are not loaded. The process flow begins with the loading of a barrel onto the elevator by a human operator at the loading station. Minor delays may occur at this stage because of the lack of consistent and repetitive operator behavior. The barrel will be transferred between baths according to its designated route. We place rinse baths between different chemical baths to prevent contamination of the baths. There is no maximum waiting time limit for rinse baths. The flow ends with the barrel being unloaded from the robot at an unloading station. The main features of electroplating line models are Robot movement times cannot be neglected. Chemical processing times are limited, transfer must occur without waiting, a bath can only process one barrel at a time, a robot can only transfer one barrel at a time, we must process products according to their route. The current, temperature, pH and liquid levels of the baths in which we perform chemical plating must be within a certain range. The electrolytic plating process can be controlled by adjusting process parameters, such as the temperature and composition of the electrolytic plating bath, current density, and the time the material spends in the bath. We can optimize these parameters to achieve the desired properties of the coating, such as thickness, adhesion, and corrosion resistance. In the automatic coating line where the coating is carried out, there are 76 baths and 6 robots that carry the product to the baths and perform the dipping process. The coating line is U-shaped. The left side of the production line, shown in Figure 1 comprises rinsing baths and the right side comprises plating baths. There are 33 bathrooms, one loading station and one unloading station in the production process of the coating process of the product in Figure 3, the data of which we used. There is a transfer station to transfer the barrel to the bathrooms on the right side after it is complete the process in the bathrooms on the left.

Fig. 1. Immersion electrolytic coating line.

The automation program automatically recorded all stages of the production processes in the electrolytic coating line shown in Fig. 1, starting from loading the barrel and ending with unloading.

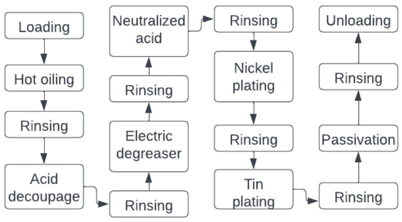


Fig. 2. Electrolytic coating stages.

Since the electrolytic plating process is very complex, faulty production is inevitable. In products coated in the electrolytic coating line; Coating defects such as bubble defect, yellowness/whiteness at the ends of the product, uncoated surface, darkening, plug mark, stain, rough/rough surface, plug stain, thin coating, black spot occur. Changes in many parameters can cause these errors such as current, voltage, temperature, pH, liquid level in the baths, and the barrel containing the product in Fig. 3 not rotating.

(a) (b)

Fig. 3. (a) Horizontal barrel and (b) coated products.

In this study, event logs of current, voltage and temperature changes taken from bath sensors of production at two different times were used. By applying process mining algorithms in ProM [14], bottlenecks, deviations, and areas where the process needs to be improved have been identified. The raw event log, which should initially comply with the production recipe, is filtered into low, normal, and high depending on the result of the parameters. That all parameters have values within the normal range indicates ideal process management and was used to discover the most appropriate process model. We then used this process model as a benchmark to detect abnormality in samples with low and high parameters.

Fig. 4 shows the process mining framework of an electroplating line. We recorded the data on the electroplating line in the ERP system. It converted the recorded raw data into an XES (extensible event stream) event log that can be used for process model exploration, visualization, compatibility, extension, and improvement in process mining tools. We visualized the created process model as a Petri net. Bottlenecks and deviations in the coating line were identified, and we analyzed the results. Compliance techniques aim to investigate whether the running process is performing as expected by comparing the observed behavior got from the event log with the behavior got from the process model. There are three main use cases of compliance checking, i.e. auditing, fraud detection, etc. Compliance checking for is the conformity check for evaluation of process discovery results/algorithms and compliance with the specification [15].

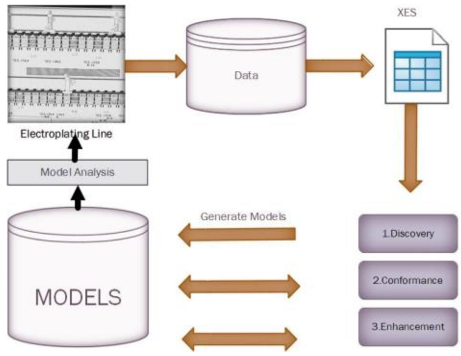


Fig. 4. Electroplating line process mining framework.

In this paper, Aksan Kalıp Ind. Trade. A.S. Process discovery algorithms were used to determine whether it was possible to detect anomalies during production using data from the 24-hour production of the company's electrolytic coating line between 13.09.2023 and 14.09.2023. Using the ProM process mining tool, a graphical view of the process was obtained using the inductive mining algorithm and the heuristic mining algorithm. Then, the requirements for optimizing the process with the basic applications of process discovery, conformity control and process mining of the discovered process were determined.

IV. Dataset Used in Our Study

The quality of the electroplating process mining depends on the quality of the data recorded by the production system. In this study, the data recorded by the automation of the real-life barrel electrolytic coating system was used. In the automation system, the current values of each bath, temperature values and liquid level changes are kept during the time the barrels spend in the baths.

To analyze the production process, data from the production process between 13.09.2023 at 12:00 and 14.09.2023 at 12:00 were used. We created an event log from raw event data under process mining. In the event log example created in Figure 5; activity, the operation of the barrel in the bath; resource, which bathroom the process is in; user shows the robot executing the transaction. Start-time gives the time when the barrel enters the bath, and complete time gives the time when it leaves the bath. Temperature, current and voltage values are the values entered the system by the operator according to the work order. It took changes in these data from the error screen of the automation and added to the event log under the time intervals.

caseid	activity	resource	user	start_time	complete_time
19766	Yukleme	1	1	13.09.2023 12:37:15	13.09.2023 12:37:35
19766	Sicak Yag Alma1	14	1	13.09.2023 12:38:01	13.09.2023 12:44:32
19766	Sicak Yag Alma2	16	1	13.09.2023 12:45:11	13.09.2023 12:54:02
19766	Durulama1	17	1	13.09.2023 12:54:41	13.09.2023 12:56:17
19766	Durulama2	18	1	13.09.2023 12:56:54	13.09.2023 12:58:32
19766	Durulama3	19	1	13.09.2023 12:59:10	13.09.2023 13:00:09
19766	Asit,Dekopaj Sicaklik N	20	2	13.09.2023 13:00:52	13.09.2023 13:07:25
19766	Durulama4	22	2	13.09.2023 13:08:04	13.09.2023 13:11:31
19766	Durulama5	23	2	13.09.2023 13:12:10	13.09.2023 13:13:09
19766	Durulama6	25	2	13.09.2023 13:13:46	13.09.2023 13:14:45
19766	Elektrikli yag alma sicaklik N	25	2	13.09.2023 13:15:24	13.09.2023 13:22:45
19766	Elektrikli yag alma Akim D	25	2	13.09.2023 13:15:24	13.09.2023 13:22:45
19766	Elektrikli yag alma SiviSeviye N	25	2	13.09.2023 13:15:24	13.09.2023 13:22:45

Fig. 5. Case study log of coating material on a barrel.

V. Material and Method

In order for process mining to be implemented successfully, accurate event logs must be created and the process mining method must be selected. In this section, inductive miner algorithm and heuristic miner algorithm, which are popular process mining process discovery techniques, were used. In this study, an Inductive Visual Miner (IvM) and Directly follows miner (DFM), an extension of IvM, were used for process mining [16]. We implemented the heuristic miner algorithm with. A general process discovery model is one in which event logs are used by the process of discovery method and we represent the output in terms of a Petri net. Petri nets are a mathematical and graphical tool used to describe synchronous, asynchronous, parallel, deterministic, and stochastic systems [17]. Graphically, it allows us to express it visually with the help of flowcharts, block diagrams, and networks. Mathematically, we can develop other models with state equations and algebraic relations.

A petri net comprises circular places, point-shaped tokens showing the state of the process, rectangular transitions, and arcs connecting places and transitions, as shown in Fig. 6. Petri nets are the best and oldest modeling language for modeling simultaneously occurring activities. Although the network structure is static, it becomes dynamic thanks to the firing rule. It comprises a $PN = (P, T, I, O, W)$ quintet.

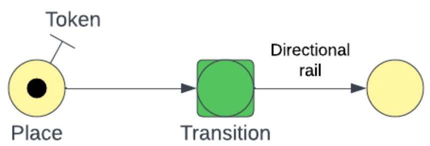


Fig. 6. Petri net parameters.

P is place set, T is transition set, I is (PxT) set of arcs from places to transitions, O is (TxP) set of arcs from transitions to places and W is indicates the weight function of the springs.

A. Alpha Mining Algorithm

It is one of the best-known process discovery algorithms. This algorithm works well in transferring simultaneous activities to the model. However, the alpha algorithm is not very good at mining. Because it does not solve noisy, sparse, incomplete, and complex route structures. Despite this, it is a good algorithm for understanding the logic of process discovery [18]. The alpha algorithm produces process models that are not robust. So, it does not guarantee durability. It does not filter out any noise by including all behavior. Thus, everything observed is included in the petri net [19].

B. Heuristic Mining Algorithm

The heuristic mining algorithm is an improvement of the alpha miner algorithm. It takes frequencies into account and filter out noisy behavior or infrequent behavior. It can detect short cycles and allow single events to be skipped. However, it still does not guarantee robust process models [20]. The heuristic algorithm sorts the occurrences in the event log and tracks the frequencies. While each event record in the alpha algorithm is taken once, in the heuristic algorithm, we calculated the frequency using event numbers.

C. Inductive Mining Algorithm

The Inductive Miner algorithm is an improvement of both alpha and heuristic mining algorithms. The algorithm was chosen for its ability to model event logs well, so that we can clearly define the process approximating reality to facilitate and improve the accuracy of the analysis. The inductive miner algorithm can deal with large event logs, largely handling unnoticed migrations during hops and traversals. A process tree is a rooted tree activity or silent activities explain whose leaves. We describe internal nodes of a process tree with operators that define the order in which we can execute activities. There are four types of operators: sequential composition, exclusive selection (xor), parallel composition, and iteration loop [21].

D. Inductive Visual Miner (IvM)

Inductive visual mining is a new demonstration of inductive mining. Discovers a process model, aligns it to the event log, and refines the resulting model. Evaluating the model becomes easier with animation and quick filtering options. When launched, IvM immediately executes a chain of analysis and visualization tasks to show the user not just a model, but traces of the event log animated on top of it, and where the log and model deviate from each other. IvM encourages the user to interact by allowing parameters to be adjusted. We restarted calculations as necessary in the background. IvM is not as feature rich as some commercial tools, but it shows that it is possible to use powerful techniques with formal guarantees in a user-friendly package [18].

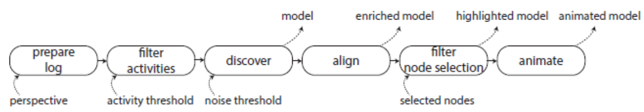


Fig. 7. Quest chain, parameters (bottom) and visual results (top)[22].

The architecture of IvM resembles a chain of analysis and visualization tasks shown in Fig. 7. To encourage exploration, the user can change any parameter. IvM can ensure that we discard the current calculation, and we restart the chain from the first task affected by the parameter change [22].

E. Direct Follow Visual Miner (DFvM)

It extends IvM with several new features compared to IvM. DFvM performs process discovery automatically and iteratively. DFvM first discovers a pattern, then aligns it to the event log to reveal deviations, and finally refines the model with frequency and performance information. Figure 10 shows an example corresponding to the process in which we execute an or b first, followed by c or d [23]. We evaluated the performance of the process model discovered in our study in terms of suitability. Fitness measures the suitability of the model to capture behavior recorded in the collected event log. This measures how many of the behaviors observed in the event log fit the process model well [2].

VI. Application, Results and Discussion

The product processed in the electroplating line proceeds sequentially from the baths where it is processed because of the line. But the current, voltage, liquid level, etc. in each bath are different. Changes in variables occur simultaneously with each other. In the event logs we use, there is a current variable in the electric degreasing, nickel plating and tin plating baths, but not in the other baths. Analysis was made of whether we processed sequentially the products in the baths under the production recipe, whether there were additions or subtractions in the bath sequence, and the liquid level changes that occurred simultaneously with the flow changes in the current baths. All analyzes were performed on a window operating system laptop with 40 GB RAM, on the ProM 6.12 open source process mining tool, using IvM, DFvM and heuristic process mining techniques, on data received from the system's ERP system to create a process mining model to detect deviations in the barrel electroplating line. has been carried out. First, it converted the data collected from the production process into event logs suitable for process mining.

The first production, which belongs to the coating process of the material in 59 cases, comprises 4418 events and 82 event classes. In Fig. 8, we see it in the workflow of the products according to time that the system shuts down between 1:30 and 3:30 and there are products that continue to be produced. To prevent oxidation in the products in the ongoing production streams, we kept the barrels in rinsing baths, as shown in Fig. 8.

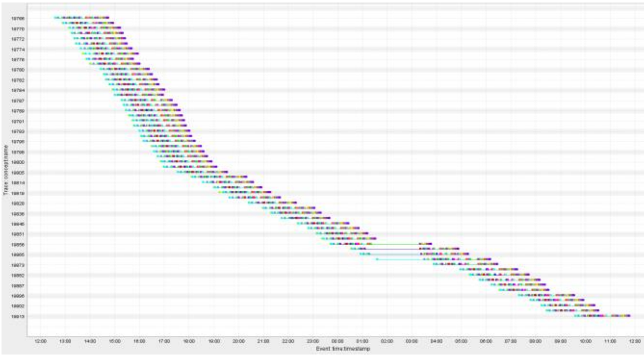


Fig. 8. Production flow of products according to time.

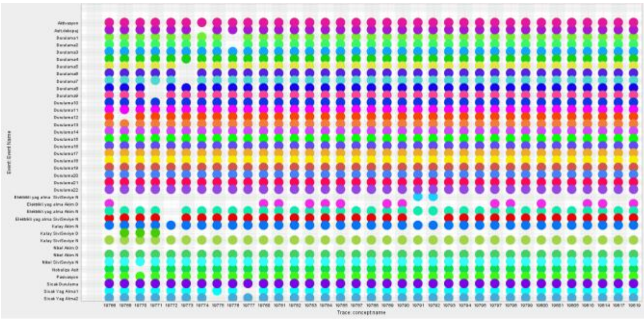


Fig. 9. Production flow of products according to time.

We give the dotted graph representation of the event correlation between the products coated in the barrels and the workflow of the coating process in Fig.9. It gave the code of the coated product on the horizontal axis, and the information of the operations performed in the baths during the coating process is given on the vertical axis. According to Fig. 9

- Acid decoupage flow in the product's production coded 19774,
- Rinse1 and Rinse2 flows in the production of product code 19776,
- Rinse12 flow in the production of product code 19769,
- In the product's production coded 19773, Rinse5, Rinse6, Rinse7 flows,
- Rinse8 and Rinse9 flows in the product's production coded 19771,
- Neutralized acid flow in the production of product code 19770,
- Hot Oil Removal2 flow in the product's production coded 19775,
- Hot Oil Removal1 flow in the product's production coded 19777,
- We observed that the electric degreasing flow was not realized in the product's production coded 19772.

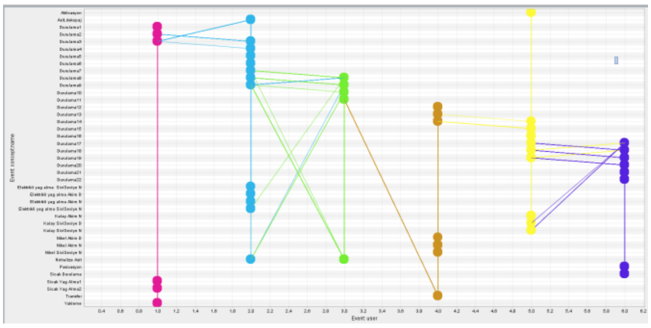


Fig. 10. Dot plot representation of the connections between robots and the bathrooms in which they operate.

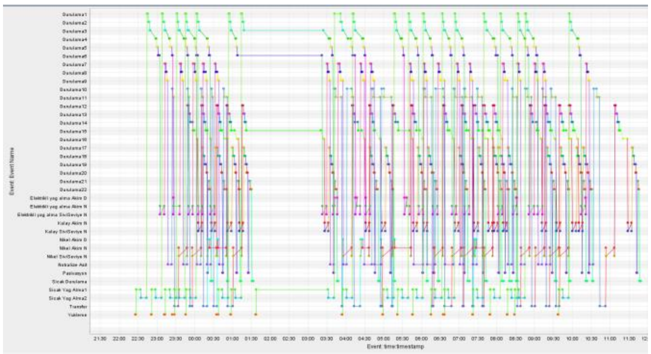
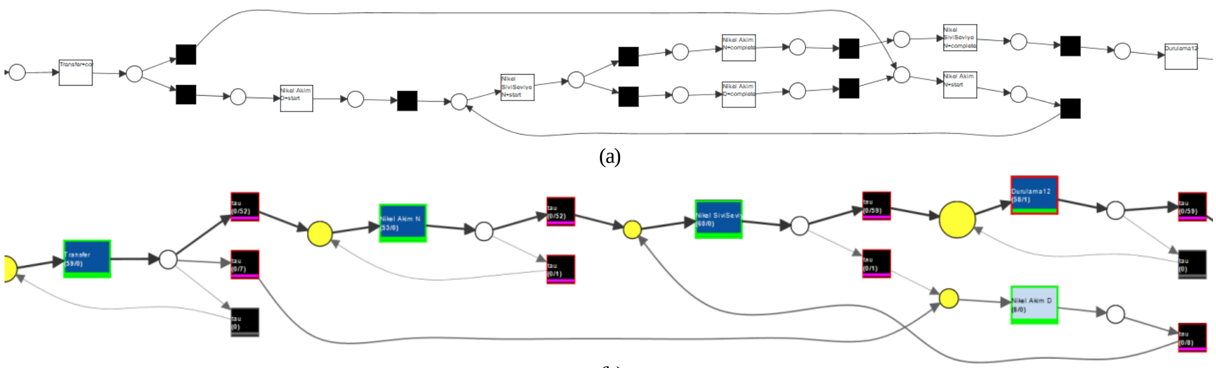


Fig. 11. Graph showing it processed which baths the products in over time.

Experiment 1: Heuristic Miner

A cross-section of the petri net modeling with the Heuristic miner algorithm of the production process is given in Fig. 12.a. While creating the petri net, the heuristic miner algorithm ensures the connections between the flows by adding silent transitions. It showed a section from the conformance analysis in Fig. 12.b. Red-framed transitions show that there are flows that do not occur. We measured the fitness value of the algorithm as 0.653.



(a)

(b)

Fig. 12. Heuristic mining paths.

Experiment 2: Inductive Miner

Because of the electroplating line, production steps must proceed sequentially. But the current, voltage, liquid level, etc. in each bath are different. Changes in variables occur simultaneously with each other. In Fig. 13, we saw anomalies in the flows in the conformance analysis made with the inductive mining algorithm. Red framed streams show streams that are not played in the model, and light blue streams show abnormal situations experienced during production. We measured the fitness value of the algorithm as 0.657.

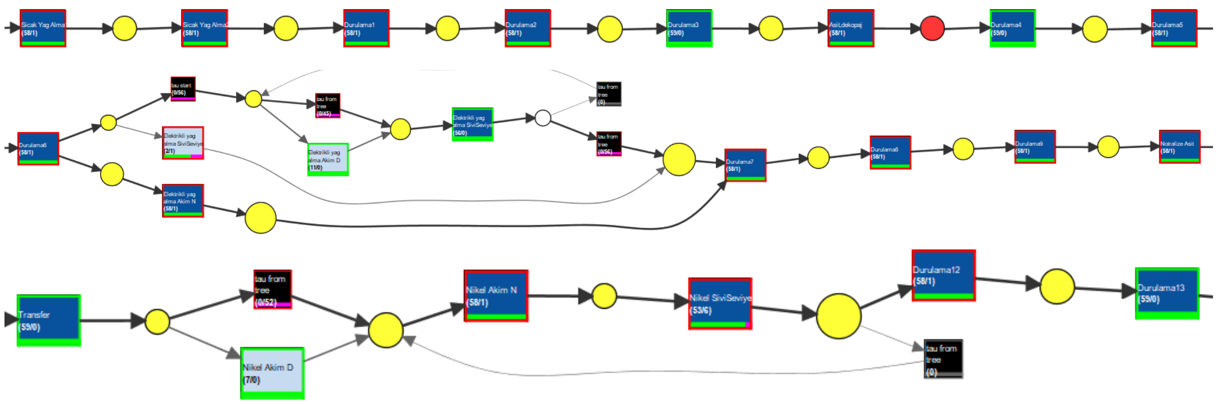


Fig. 13. Inductive Miner conformance analysis.

Experiment 3: Inductive Visual Miner

The purpose of using IvM is to ensure the robustness of the model so that it can represent all flow paths throughout the lifecycle of the discovered model. In Figure 18, it developed a process model using IvM to follow the paths of the barrel electrolytic coating line in the production flow. In Fig. 14, from left to right, the flow pattern of electroplating production started with 59 cases occurring sequentially. Then, the events occurring simultaneously in the chemical coating baths are shown as parallel paths. We can see that the current decreased in the electric degreasing bath 22 times, the current decreased in the nickel bath 7 times, and the liquid level decreased in the tin bath 3 times.

It identified flows where deviations and bottlenecks occurred during the execution of the process; these are marked in red in Fig. 15. A red color with a 1 in the model shows we skipped once the relevant activity in the event log, but the model shows we should execute it. Red-colored loops show that there are flows that should not be in the model. We measured the fitness value of the algorithm as 0.990.

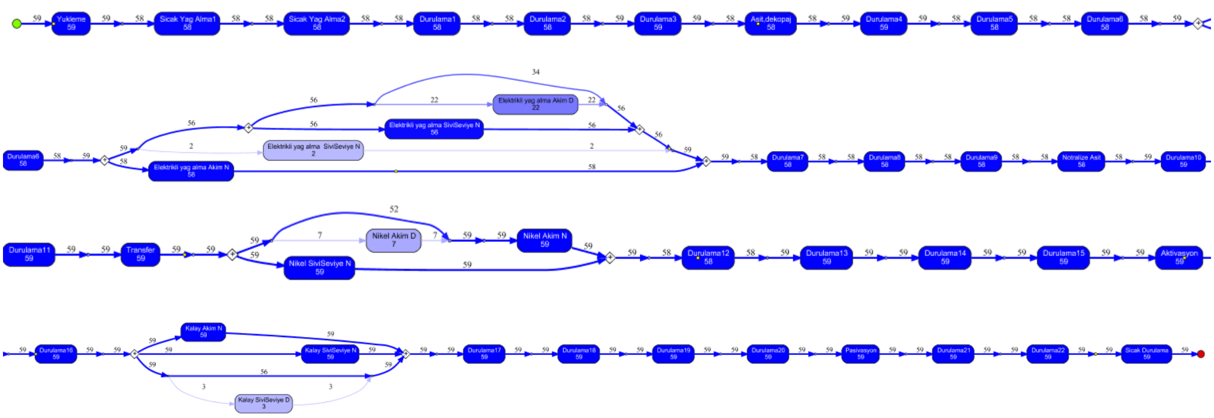


Fig. 14. Inductive visual miner paths.

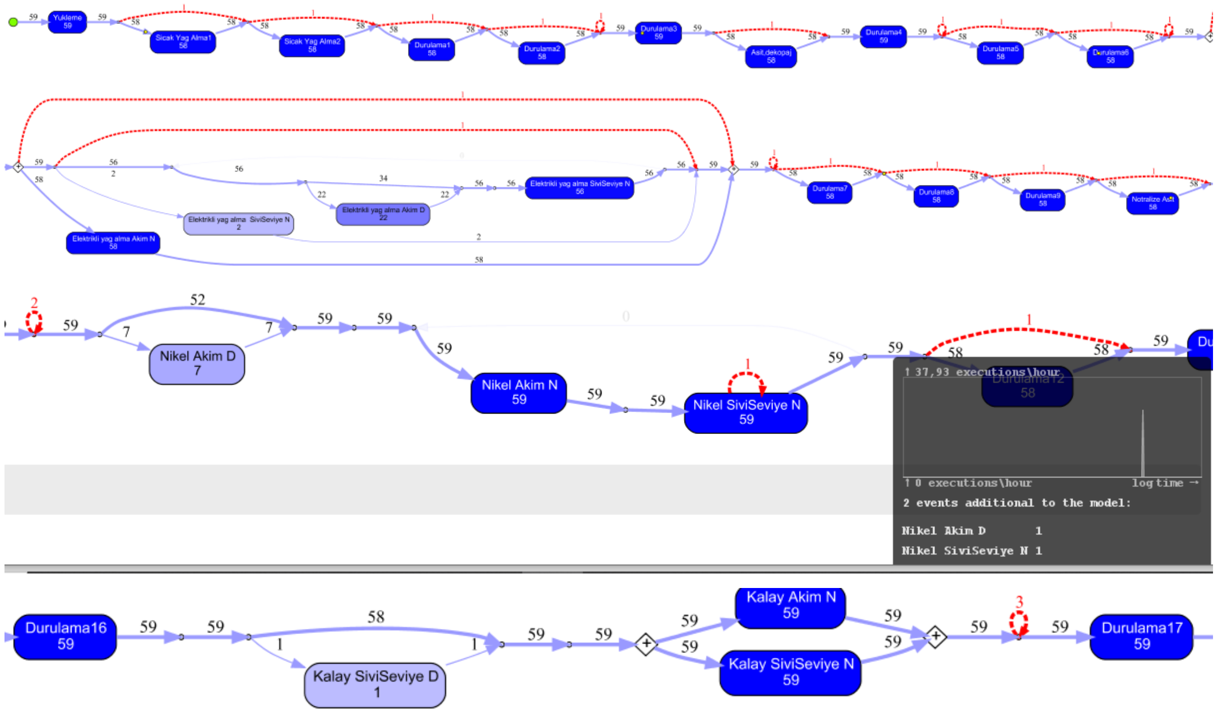
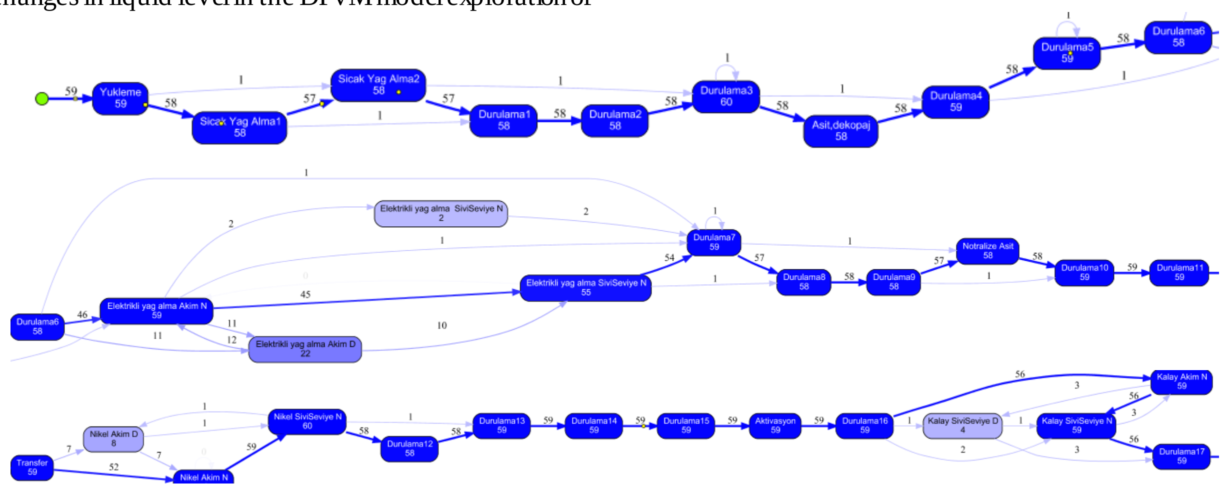


Fig. 15. Inductive visual miner paths and derivations.

Experiment 4: Direct Follow Visual Miner

Direct trace visual miner (DFvM) [16], an extension of IvM with many new features compared to IvM, performs process discovery automatically and iteratively. Fig. 16.a shows the relationships between current changes in the baths and changes in liquid level in the DFvM model exploration of our event log. The area marked in red shows deviations. The red marked areas in Fig. 16.b show deviations in the model. DFvM tracked two path deviations in the discovered process model, unlike the IvM inductive miner and heuristic miner, which detected multiple path deviations. Compared to other models, we found the DFvM model to be more robust.



(a) DFvM paths

(b) Deviations

Fig. 16. DFvM paths and deviations.

TABLE I. COMPARISON OF PROCESS MINING ALGORITHMS

Event Logs	Algorithms	Fitness
Production event log	Inductive Miner	0.657
	IvM	0.990
	DFvM	0.999
	Heuristic Miner	0.653

When the results of the algorithms are evaluated in terms of suitability in Table 1, DFvM with a suitability of 0.999 showed better performance, followed by IvM with a suitability of 0.990.

VII. CONCLUSIONS

Process mining techniques enable organizations to gain insight into their processes by using event data collected during the execution of these processes. Process mining techniques focus on three key areas: (i) process discovery, which deals with the discovery of process models based on the behavior of events, (ii) conformance analysis, which identifies discrepancies between the discovered process model and actual process executions, and (iii) improvement of the process model through learnings from conformance analysis. Creating a feedback mechanism for process improvement. Article, Aksan Kalıp San. Tic. Using the data of A.S.'s automatic barrel electrolytic coating line, we show the suitability values of the models created by process discovery methods and the deviations. Since the data received from the ERP system and sensors were not suitable for process mining event logs, we rearranged the data. In the study, the 24-hour production of the barrel electrolytic coating line was modeled with petri nets using heuristic miner, inductive miner, inductive visual miner and direct visual miner process discovery algorithms. When the experimental results got are examined, the performance ranking of the algorithms according to their fitness values is DFvM, IvM, Inductive Miner and Heuristic Miner, respectively. DFvM and IvM are better at modeling changes that occur during production. Before the quality control step, the defectiveness of the product can be predicted with process mining and, depending on the situation, we can send the product to package or scrapped if it is defective. When creating process mining event logs, we should conduct research to use machine learning algorithms with process mining to classify data. We should explore automated process monitoring tools to enable real-time detection and correction of errors in production.

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REFERENCES

[1] F. Chetouane, "Electroplating line flexible control using p-time petri nets modeling and hoist waiting times calculation," Int. J. Ind. Eng. Theory Appl. Pract., vol. 15, no. 3, pp. 266–277, 2008.

[2] H. Alqaheri and M. Panda, "An Education Process Mining Framework: Unveiling Meaningful Information for Understanding Students' Learning Behavior and Improving Teaching Quality," Inf., vol. 13, no. 1, 2022, doi: 10.3390/info13010029.

[3] D. Fahland, Process Mining over Multiple Behavioral Dimensions with Event Knowledge Graphs, vol. 448. 2022. doi: 10.1007/978-3-031-08848-3_9.

[4] W. Van der Aalst, Process mining: Data science in action. Berlin Heidelberg: Springer-Verlag, 2016.

[5] W. van der Aalst, "Decomposing Petri nets for process mining: A generic approach," Distrib. Parallel Databases, 2013, [Online]. Available: http://link.springer.com/article/10.1007/s10619-013-7127-5

[6] W. Van Der Aalst et al., "Process mining manifesto," Lect. Notes Bus. Inf. Process., vol. 99 LNBIP, no. PART 1, pp. 169–194, 2012.

[7] J. Maeyens, A. Vorstermans, and M. Verbeke, "Process mining on machine event logs for profiling abnormal behaviour and root cause analysis," Ann. des Telecommun. Telecommun., vol. 75, no. 9–10, pp. 563–572, 2020, doi: 10.1007/s12243-020-00809-9.

[8] Z. Tariq, D. Charles, S. McClean, I. McChesney, and P. Taylor, "Anomaly Detection for Service-Oriented Business Processes Using Conformance Analysis," Algorithms, vol. 15, no. 8, pp. 1–25, 2022.

[9] O. T. Baruwa, M. A. Piera, and A. Guasch, "Deadlock-free scheduling method for flexible manufacturing systems based on timed colored petri nets and anytime heuristic search," IEEE Trans. Syst. Man, Cybern. Syst., vol. 45, no. 5, pp. 831–846, 2015, doi: 10.1109/TSMC.2014.2376471.

[10] M. Mabed, F. Bousseau, and M. Bourcerie, "Modeling Dynamic Complex Systems: Application to an Electroplating Line," IFAC Proc. Vol., vol. 33, no. 17, pp. 59–64, 2000, doi: 10.1016/s1474-6670(17)39375-8.

[11] K. H. Han, S. B. Lee, and I. K. Hong, "Barrel plating process specification for undercoating with copper cyanate," J. Ind. Eng. Chem., vol. 18, no. 3, pp. 888–897, 2012, doi: 10.1016/j.jiec.2011.11.066.

[12] "The Barrel Electroplating Process," WebPage. https://heplating.com/plating_methodsbarrel_electroplating/

[13] S. Corp, "PLATING PROCEDURES by Raymund Singleton," Met. Finish. 99, Suppl. 1, pp. 340–359, 2001.

[14] "ProM 6.12." https://promtools.org/prom-6-12/

[15] A. Berti and M. Sc, "Skeleton in Python Bachelor ' s Thesis," 2021.

[16] S. J. J. Leemans, E. Poppe, and M. T. Wynn, "Directly follows-based process mining: Exploration & a case study," Proc. - 2019 Int. Conf. Process Mining, ICPM 2019, pp. 25–32, 2019, doi: 10.1109/ICPM.2019.00015.

[17] T. Murata, "Petri Nets : Properties , Analysis and Applications," Proc. IEEE, vol. 77, no. 4, pp. 541–580, 2015.

[18] D. R. Ferreira, A primer on process mining : practical skills with Python and Graphviz Edition. 2020. [Online]. Available: http://www.springer.com/series/10189

[19] Ş. Sevim, "Süreç madencili̇ği̇ yöntemi̇ ile satin alma sürecinin analiz edilmesi," 2021.

[20] A. J. M. M. Weijters, W. M. P. van der Aalst, and A. K. A. de Medeiros;, "Process Mining with the HeuristicsMiner Algorithm," Beta Work. Pap., 2006.

[21] T. Pohl, "An Inductive Miner Implementation for the PM4PY Framework," pp. 1–66, 2019.

[22] S. J. J. Leemans, D. Fahland, and W. M. P. Van Der Aalst, "Process and deviation exploration with inductive visual miner," CEUR Workshop Proc., vol. 1295, no. September, pp. 46–50, 2014.

[23] S. J. J. Leemans, "Inductive visual Miner manual," pp. 1–16, 2017, [Online]. Available: http://promtools.org.

[24] M. Mayr, S. Luftensteiner, and G. C. Chasparis, "Abstracting Process Mining Event Logs from Process-State Data to Monitor Control-Flow of Industrial Manufacturing Processes," Procedia Comput. Sci., vol. 200, pp. 1442–1450, 2022, doi: 10.1016/j.procs.2022.01.345.