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Analysis Study for Rabobank Group ICT Incident by using Fuzzy and Heuristic Miner in Process Mining

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Abstract
The decline in the marketing volume of Rabobank Group ICT is a serious incident as it can hinder the implementation of an increasing number of software releases for business development. The Service Desk Agent records the activities that occur to find out the problems experienced in the form of an event log. Process mining can be used to generate process model visualizations based on event logs to explicitly monitor the business. Fuzzy Miner and Heuristic Miner algorithms can be used to handle complex event logs. In this study, an analysis of the Rabobank Group ICT incident was carried out with process mining using the Fuzzy Miner and Heuristic Miner algorithms. Process mining is done by discovery, conformance, and enhancement. Based on the results of the study, it is known that the division of the work area is not good enough to cause a team to work on a lot of events while there are other teams that only work on one event. Therefore, it is necessary to have a clear and balanced division of domains and workloads so that incidents do not recur.

Keywords
Rabobank Group ICT, Process Mining, Fuzzy Miner, Heuristic Miner

I. Introduction

A certain business will always focus on business development such as increasing the number of production and marketing or improving services with effective and efficient processes [1],[2]. Like Information and Communication Technologies (ICT) companies in general, Rabobank Group ICT needs to implement an increase in the number of software releases in its business development efforts by taking into account the amount of marketing that occurs. In 2013 it was reported that the marketing volume of Rabobank Group ICT software decreased drastically. Rabobank Group ICT is an ICT division of the Dutch financial services company Rabobank Group [3].

As an effort to handle incidents that occur, Rabobank Group ICT has implemented the Information Technology Infrastructure Library (ITIL) process to produce planned changes [4]. The system change starts with an analysis of past errors to be able to predict future changes in workload on the service desk/IT operations so as to provide better efficiency in implementing Rabobank Group ICT software releases [5], [6].

Incident management is a concern with process mining which can identify efficiency opportunities in complex business functions to improve risk improvement and management [7], [8], [9]. Incident cases that occurred at Rabobank Group ICT can be analyzed with event log data provided by BPI Challenge 2014. The activity log comes from an anonymous Rabobank Netherlands Group ICT containing detailed records from an ITIL service management tool called HP Service Manager. Service Desk Agent (SDA) records activities that occur to find out problems experienced by customers, but not all problems can be understood and resolved, so incident activity records are made in the form of event logs that can be processed more deeply by the assignment group [3], [10].

Process mining is one of the techniques that can be used to generate process model visualizations based on event logs that can be further processed to monitor business explicitly down to very small details of log activity [11],[12],[13]. Process mining plays a role in modeling and analyzing processes by finding, monitoring, and improving the actual process by extracting knowledge from available event logs. Process mining can define the model process as well as the relationship between the actual process and the data. There are three stages of the mining process, namely discovery, conformance, and enhancement [14].

Discovery plays a role in analyzing event log data by creating an initial process model without using a priori information. Conformance checking is used to check whether the model created matches the actual event. Enhancement extends or augments the process model with real-life information. The enhancement process can be carried out in two forms, namely repair or extension. Repair is done by modifying the model to better reflect reality, while the extension is done by adding a new perspective based on the available event logs and the resulting process model [5].

The discovery process is done with Disco tools while conformance with ProM. Disco is also used to sort out unused data, remove noise, and filter out invalid information to the endpoint [15]. ProM is used to implement the algorithm on the model generated by Disco [16]. The algorithm used in process mining for the analysis of Rabobank Group ICT incidents is the Fuzzy Miner Algorithm and the Heuristic Miner. Event log data on Rabobank Group ICT incidents is complex real-life company data that requires a special approach to handling it. Fuzzy Miner and Heuristic Miner algorithms can be used in process mining to be able to handle complex event logs so that they can be observed properly [17],[18]. Disco and ProM are tools that can be used in data processing with statistical capabilities, filtering functions, and process map generators on Disco as well as innovative process mining capabilities on ProM [19],[20],[21].

This study aims to provide an analysis of the Rabobank Group ICT incident based on the 2014 BPI Challenge event log with process mining using the Fuzzy Miner Algorithm and Heuristic Miner through the Disco and ProM tools to predict the workload for the service desk so that improvements can be made to the implementation of software releases as Rabobank Group ICT business development efforts.

In a previous study "Analysis and Implementation of Process Mining with Heuristic Miner Algorithm Case study: Event logs of Rabobank Group ICT Netherlands" an incident analysis was carried out on the event log of Rabobank Group ICT with the Heuristic Miner algorithm using Filter Log using Simple Heuristics on ProM. Based on the test results, it is known that the ideal process model is obtained by setting the positive observation threshold parameter of 1000, relative to the best 0.05, and the dependency threshold value of 0.9. The parameter that has the greatest influence is the positive observation threshold. This is because these parameters have the ability to filter data with very small trace frequencies so that they are not processed in the mining process [3].

Another study "Analysis and Implementation of Process Mining Using Fuzzy Mining (Case Study: Data BPI Challenge 2014)" which showed that the use of a threshold in the simplification process resulted in good conformance with a low preserve threshold, a high utilization ratio. high, and the edge cutoff and node cutoff are low. Based on the test, the process model with the best conformance is a preserve threshold of 0.05, utility ratio of 0.85, edge cutoff of 0.05, and node cutoff of 0.05 [10].

Based on the results of previous studies, it is known that the review of process mining results only focuses on measurement parameters and does not provide process models regarding incidents that occur. For this reason, this study provides a process model from the parameters that have been determined in previous studies to find out the problems that occur in the Rabobank Group ICT incident from all aspects of the event log that affect changes in the workload of the service desk/IT operations. In addition, additional tools, namely Disco, are used to generate valid data up to the endpoint by filtering and reducing the noise before entering ProM. In addition, process modeling in ProM with Heuristic Miner is carried out with interactive Data-aware Heuristic Miner (iDHM) with the best parameter settings for event logs automatically (Mannhardt et al., 2017). This setting will be compared with the results of manual trials conducted [3] with a Filter Log using Simple Heuristics on ProM.

II. METHODS

The decline in the number of product marketing is a serious problem and an obstacle to increasing the number of software releases at Rabobank Group ICT. This affects the business development of Rabobank Group ICT. For this reason, it is necessary to analyze to overcome the incident that occurred. The Service Desk Agent (SDA) records the activities that occur in the form of an event log to be analyzed and given solutions to overcome the incidents that occur. Process Mining is one way that can be used. The complex data makes the Fuzzy Miner and Heuristic Miner algorithms chosen to provide a process model for incidents that occur. Thus, improvements can be made to the IT service desk/operations to help Rabobank Group ICT return to a steady state.

The process mining system was built by creating an initial process model at Disco and implementing the Fuzzy Miner algorithm with Mine for a Fuzzy Model and the Heuristic Miner algorithm with interactive Data-aware Heuristic Miner (iDHM) on ProM on the Rabobank Group ICT incident log activity. The output built is a process model that can be used for evaluation by Rabobank Group ICT (Fig. 1).

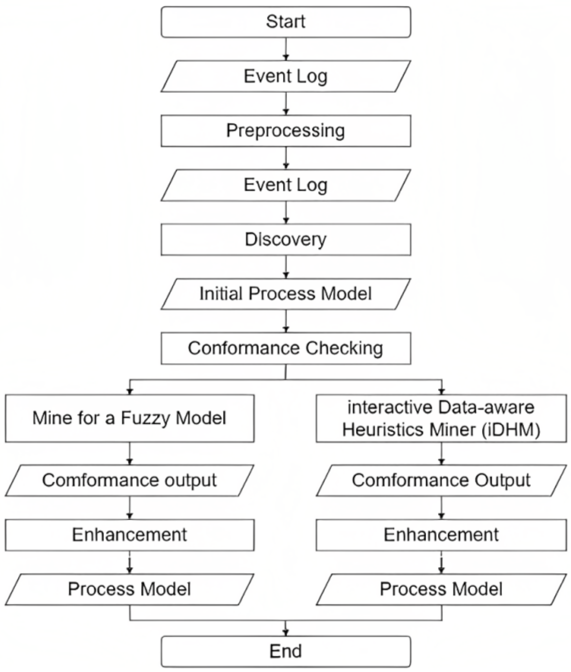

Fig. 1. Modeling flowchart

A. *Heuristic Miner*

Heuristic Miner is an algorithm in process mining that focuses on control flow to generate process models in Heuristics Nets format for certain event logs. The starting point of the heuristics miner is the construction of a dependency graph [12]. Heuristic Miner can handle noise and can be used to express large events in the event log. Heuristic Miner only considers the sequence of events in a case without considering the sequence of events between cases. Event data is sorted by timestamps from earliest to newest. Heuristic Miner extracts a C-net process model, with a finite set of activities and dependency relationships from those activities [22].

The steps used in forming the process model with the Heuristic Miner algorithm include:

1. Create a dependency graph matrix to store the number of dependency relationships between two activities.

2. Determine the Dependency threshold, Positive Observation threshold, Relative to best threshold as the basis for selecting the dependency relation that will be raised in the process model.

3. Checks if there is a short loop (length-one-loop or length-two-loop).

4. Determine parallel relations (XOR or AND) between activities.

5. Process models can be formed [22].

The Heuristic Miner algorithm can handle spaghetti processes problems by focusing on the number of occurrences of relations between activities with one another in the event log in forming the process model. Spaghetti processes are event logs that have too many complicated relationships making them difficult to read. The relationship between activities with a small number will not appear in the process model formed by the Heuristic Miner algorithm. The advantage of the Heuristic Miner algorithm is that it can display repetitive activities in the form of length-one-loop and length-two-loop if the event log contains these relations. The results of the process model can be converted into a Petri net that can display parallel relations such as XOR and AND. The disadvantage of the Heuristic Miner algorithm is that the number of relations between activities that have a small occurrence in the event log can be considered a disturbance so that these relations cannot appear in the process model [22].

The implementation of the heuristic miner is to analyze the software structure and implementation information. Source code repository mining enables an understanding of how development teams work together during software system development and makes it possible to perform historical and evolutionary analysis of source code elements and structures [23].

B. *Fuzzy Miner*

The Fuzzy Miner Algorithm is an algorithm that is intended for complex real-life log data. The process model generated at the discovery stage can be simplified by the Fuzzy Miner algorithm to avoid spaghetti processes through the simplification process by paying attention to the right variables to get good conformance [10]. In its implementation, the Fuzzy Miner algorithm uses the concept of a road map as a parable to visualize the resulting model. In the concept of a roadmap, components that have a less important role will not be displayed like small roads on the map. Several small cities that are still in one part of a big city will be combined, so the right decision criteria are needed as a basis for the simplification and visualization of a process model [24].

There are two basic matrices used, namely significance and correlation. Significance can be determined for activities (nodes) and relationships (edges) by measuring the value of relative importance so that the level of importance can be determined. Correlation is used to determine the relationship that takes precedence over activities by measuring how close the relationship between two activities is [25]. In detail, the measurements of significance and correlation include:

1) *Log-Based Process Metrics*: In measuring significance, there are two categories: unary significance and binary significance. The significance that is measured for activities in the process is called unary significance, while the significance that measures the relationship in the process is called binary significance. Correlation is often called "binary correlation"

because it is only used to estimate the relationship between two activities or events so that they can find out how closely related one event class is to another event class. Of the three matrices (unary significance, binary significance, and binary correlation), the first will provide information to simplify the initial model and will be used to build process models adaptively (Günther & van der Aalst, 2007).

2) *Adaptive Graph Simplification Process*: In the graph simplification process with Fuzzy Miner, there are three processes: binary conflict resolution, edge filtering, and node aggregation and abstraction. The binary conflict resolution process is influenced by 2 parameters, namely the preserve threshold and the ratio threshold. The edge filtering process is influenced by 2 parameters, namely the edge cutoff and utility ratio. Meanwhile, the node aggregation and abstraction process is influenced by the cutoff node parameter [26].

Fuzzy miner is also implemented to handle heterogeneous logistics learning processes. Process mining is able to extract the learning path into the process model from beginning to end and can present process variants. Because there is an outlier based on the number of occurrences when a group of students interact with the learning outcomes, the outlier data must be removed first to get the appropriate results [27].

III. Results and discussion

A Preprocessing is done by cleaning data such as noise reduction, removing duplication of data, removing unused attributes, and data transformation. There are 466,737 data with seven initial attributes that are displayed in the event log in CSV format, namely Incident ID, Datetestamp, IncidentActivity _ Number, IncidentActivity_ Type, KM number, Assignment Group, and Interaction ID (Table I). In this process, 4 main attributes are used to be processed for modeling, namely Case ID, Activity, Timestamp, and Originator.

TABLE I.
INITIAL EVENT LOG DATA

Incident ID	DateStamp	IncidentActivity_Number	IncidentActivity_Type	Assignment Group
IM0000004	07/01/2013 08:17	001A3689763	Reassignment	TEAM0001
IM0000004	04/11/2013 13:41	001A5852941	Reassignment	TEAM0002
IM0000004	04/11/2013 13:41	001A5852943	Update from customer	TEAM0002
IM0000004	04/11/2013 12:09	001A5849980	Operator Update	TEAM0003
IM0000004	04/11/2013 12:09	001A5849979	Assignment	TEAM0003
IM0000004	04/11/2013 13:41	001A5852942	Assignment	TEAM0002

Case ID is an identity that determines the scope of the process. In this study, the scope of the process is the activity in the incident section, so that the Incident ID column is used as Case ID. Each Case ID represents a process that is different from other processes. Case ID will be simplified into numeric form for easier reading. Activity, is an attribute with a value that describes the stages of the running process. The attribute that represents the activity is the IncidentActivity_Type attribute. Each Case ID has several ongoing activities such as Reassignment, Update from customer, Assignment, and others.

Timestamp is an attribute that marks the time the activity occurs in each case. Each activity has its own timestamp. Timestamp is very important to determine the order in which an activity occurs from start to end of a Case ID. The timestamp attribute is indicated by Datetamp which has a time value in the form of the date and time the activity occurred.

Originator, is an attribute that indicates the actor or person in charge of each activity that takes place. In the event log that is used as the originator is the Assignment Group attribute which contains the name of the team as the perpetrator of each activity (Table II).

TABLE II.
FINAL EVENT LOG DATA

Case ID	Timestamp	Activity	Originator
IM0000004	07/01/2013 08:17	Reassignment	TEAM0001
IM0000004	04/11/2013 13:41	Reassignment	TEAM0002
IM0000004	04/11/2013 13:41	Update from customer	TEAM0002
IM0000004	04/11/2013 12:09	Operator Update	TEAM0003
IM0000004	04/11/2013 12:09	Assignment	TEAM0003
IM0000004	04/11/2013 13:41	Assignment	TEAM0002

A. Discovery

Discovery data is done with Disco to get insightful event log data (Fig. 2). The steps taken in the discovery process include importing data, setting parameter attributes, displaying the process model, and exporting the results of the discovery in MXML format. The process model generated at the discovery stage is called the initial process model, which is obtained based on a matrix with cases transformed into activity nodes. Initial process models.

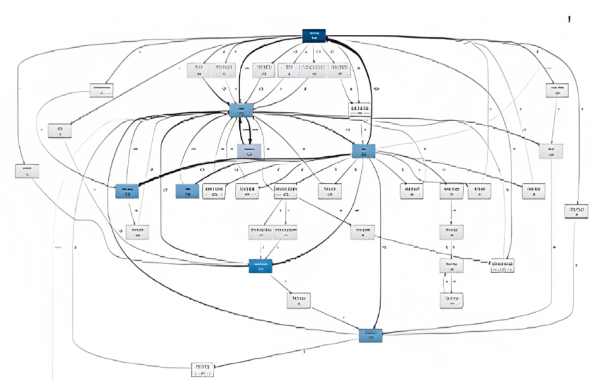

Fig. 2. Initial process model

The initial result process model is in the form of spaghetti processes caused by too many relationships between activities.

The process model with too many relations makes it difficult for the reader to analyze the graph because it is difficult to draw the main conclusions obtained. Spaghetti processes can be simplified through a graph simplification process by applying the Heuristic Miner and Fuzzy Miner algorithms at the conformance stage using ProM.

B. Conformance Checking

Conformance checking is the validation stage in the initial process model generated against the event log data used. The process model generated in the discovery stage can be simplified by the Fuzzy Miner and Heuristic Miner algorithms to avoid spaghetti processes through the simplification process. The application of the Heuristic Miner in ProM is carried out using an interactive Data-aware Heuristic Miner (iDHM), while the application of the Fuzzy Miner is carried out using Mine for a Fuzzy Model (Fig. 3).

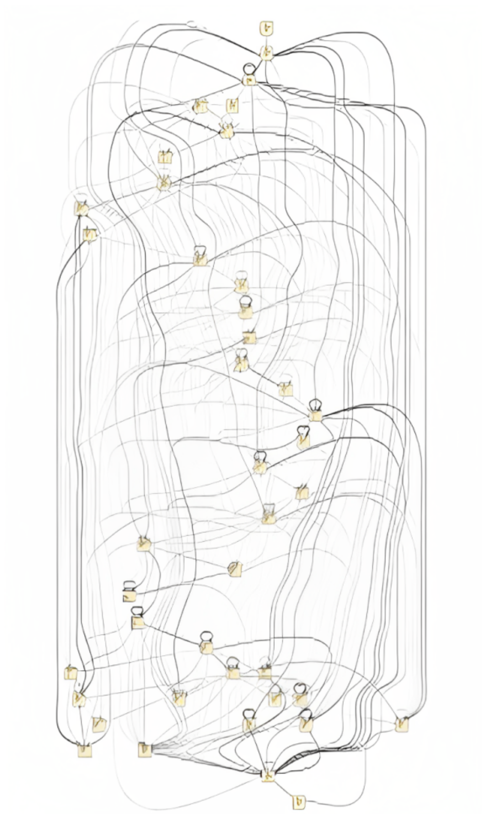

Fig. 3. Fuzzy Miner process model without scenario

C. Mine for a Fuzzy Model

In the process modeling with the Fuzzy Miner algorithm, a process model without scenario is made and several working scenarios are applied to determine the best conformance (Fig 4). Scenario implementation is done by finding the best log conformance value with a combination of the Preserve Threshold, Ratio Threshold, Edge Cutoff, Utility Ratio and Node Cutoff parameters. Based on research conducted by [10], the process model with the best conformance is carried out by preserving threshold 0.05, utility ratio 0.85, edge cutoff 0.05, and node cutoff 0.05 [3].

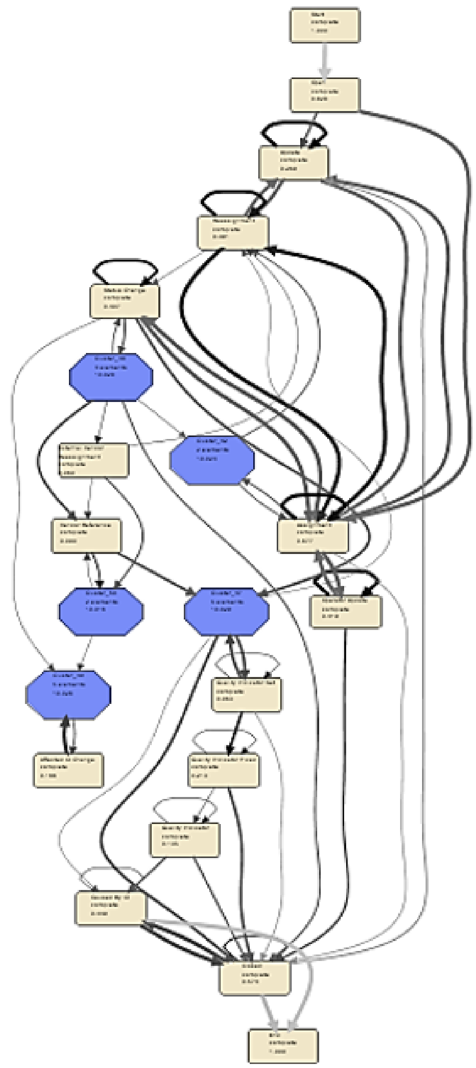

Fig. 4. Fuzzy Miner process model with scenario

Blue labels indicate clusters and yellow labels indicate cluster elements or log activity performed (Fig. 4). The resulting process model shows that there are 5 main clusters produced, namely cluster 42, cluster 47, cluster 48, cluster 49, and cluster 50. Activities that have a high correlation with other activities are assignments from cluster 42 (Table III).

TABLE III.
DISTRIBUTION OF CLUSTER ELEMENTS

Case ID	Timestamp	Activity	Originator
IM0000004	07/01/2013 08:17	Reassignment	TEAM0001
IM0000004	04/11/2013 13:41	Reassignment	TEAM0002
IM0000004	04/11/2013 13:41	Update from customer	TEAM0002
IM0000004	04/11/2013 12:09	Operator Update	TEAM0003
IM0000004	04/11/2013 12:09	Assignment	TEAM0003
IM0000004	04/11/2013 13:41	Assignment	TEAM0002

D. Interactive Data-aware Heuristic Miner (iDHM)

In the application of the Heuristic Miner algorithm, an interactive Data-aware Heuristic Miner (iDHM) is used in ProM to generate the best dependency values automatically. iDHM provides interactive exploration of the parameter space and includes a built-in conformance check to diagnose the quality of the found model. Thus, it is easier to explore large parameter spaces and directly find fit problems of the model found, for example, deviant and missing behavior in event logs. Furthermore, iDHM uses attribute data from event logs to reveal conditional dependencies that occur infrequently [28].

Parameters obtained from iDHM measurements include the observation frequency threshold of 0.1, dependency measure threshold of 0.9, binding frequency threshold of 0.1, and condition quality threshold of 0.5. These parameters are in accordance with the best results which shows the accuracy of the parameters in iDHM without performing a number of dependency variations on the test [10]. The process model is visualized in C-net with clear semantics.

The process model produced by Heuristic Miner is in the form of a dependency graph (Fig. 5.). The dependency relationship between two activities represents the causal dependence of one activity on the other which is represented as a directed edge between the two activities. Only strong dependencies that exceed the configured dependency threshold and are observed more frequently than the included configuration observation frequency threshold. The data perspective is taken into account when discovering the control flow of a process. Classification techniques are used to reveal data dependencies between activities. These data dependencies are used to distinguish random noise from conditional dependencies that occur infrequently. The technique is based on a control flow perspective and ignores infrequent behavior such as noise.

Conditional dependencies can provide insight for process analysts as they can indicate solutions and deviations from normal process behavior. iDHM only includes conditional dependencies whose underlying data state quality exceeds the configured state threshold. Disconnected points represent exclusive splits (XOR) and connected points represent parallel splits (AND). Decision rules can be filtered based on the decision rule quality threshold. C-Net conformance checking

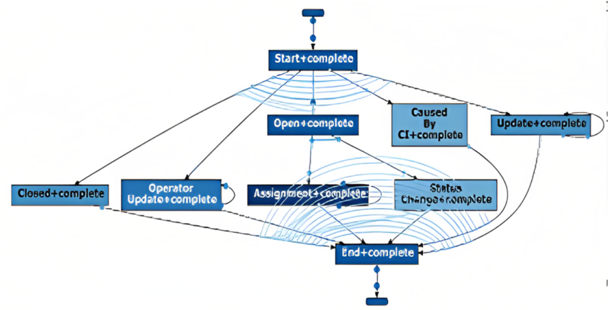

Fig. 5. Heuristic Miner process model

techniques and event logs to project frequency on activities and bindings. Activities and bindings are color coded based on how often they occur according to the event log. The size of the binding dots also scales with the frequency with which they occur. A small circle of the respective color to the top left of the activity to indicate a conformance issue.

The process model obtained shows the dependence of assignments and status changes on open activities. There are compatibility issues with update, assignment, and operator update activities. This is because the Heuristic Miner trims some data with low frequency to be displayed on the process model, while in the process model generated by Fuzzy Miner it is known that the assignment has a large number of relationships with other activities.

E. Enhancement

The enhancement process is carried out by analyzing the originator. Based on the results of conformance, it is known that the process model shows a tendency for workloads in the assignment process, so an analysis is carried out on the division of teams to make assignments to the process. The analysis is done by knowing the division of workload for each team in the assignment process. Based on the event log data used, there were 88,502 assignment activities performed.

The distribution of the frequency of assignment activities carried out for each team shows that there is an imbalance of tasks in the assignment process (Fig. 6). Team008 does more assignments than Team0241. This causes the services provided by Rabobank Group ICT to be less than optimal due to the uneven workload. For this reason, it is recommended to pay more attention to the division of workload on each IT service desk/operations team so that the services provided are more optimal and increase customer trust so that they can increase the amount of marketing.

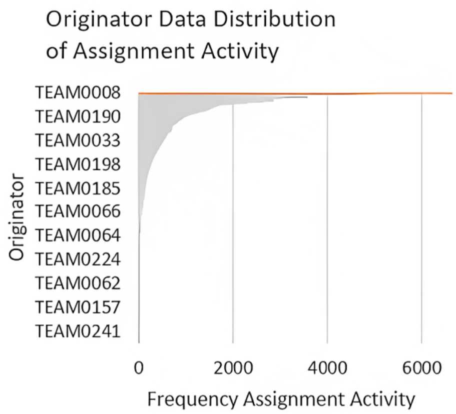

Fig. 6. Distribution of assignment activity frequency

IV. Conclusion

Based on the testing result of the Rabobank Group ICT incident event log with process mining, it is shown in a spaghetti process model at the discovery stage generated by Disco and ProM. The use of the fuzzy miner and heuristic miner algorithms with the simplification process produces a graph of the relationship that can be observed. iDHM is used on the heuristic miner with direct conformance capability and automatic best dependency settings with parameter observation frequency thresholds of 0.1, dependency measure thresholds of 0.9, binding frequency thresholds of 0.1, and condition quality thresholds of 0.5. In Fuzzy Miner, the preserve threshold value is 0.05, the utility ratio is 0.85, the edge cutoff is 0.05, and the node cutoff is 0.05. In terms of incidents, it is known that the division of the work area is not good, causing a team to work on a lot of events while other teams only work on one event. Therefore, it is necessary to divide the team with clear and balanced areas and workloads in business processes so that incidents do not recur.

Conflict of interest

The authors have no conflict of relevant interest to this article.

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