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Improved fuzzy miner algorithm for business process discovery

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ABSTRACT

Return material authorization (RMA) is a process in which a company decides to repair or replace customer's defect product during the warranty period. To execute RMA, both company and customer obliged to follow standard operating procedure (SOP) which usually consists of many business processes of a company well. As the business process could cause inefficiencies, a company should improve their business process regularly. The best way is using process discovery. This research proposes a new improved fuzzy miner algorithm to represent binary correlation between activities. This new algorithm utilizes binary significance and binary correlation equally to acquire fuzzy model. While the original fuzzy miner algorithm uses various binary correlation metrics, the improved fuzzy miner algorithm uses only one metric and could capture the fuzzy model, accurately based on the event logs to capture more accurate business process model. In this research, ProM fuzzy miner is used as a comparison to the proposed improved time-based fuzzy miner. The results showed that the improved algorithm has higher value on conformance checking and able to capture business process model based on time interval, by using only time-interval significance as a binary correlation metrics.

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1. INTRODUCTION

Return material automatically (RMA) is a process to return the device to the company if damage occurs [1]. This return aims to repair or replace the device, where the decision rests with the company. RMA could be considered a project, where it consists of interrelated activities that should be done in particular sequence or order to complete the entire task, aiming for the goal. In this project, the company needs to check the device to identify the damage and make a repairing or replacement decision. This business process has the potential to cause bottlenecks in the flow, as well as the emergence of unnecessary excessive costs.

To execute RMA, both company and customer obliged to follow standard operating procedure (SOP) which usually consists of many business processes. As the business process could cause inefficiencies, a company should improve their business process regularly. The best way is using process discovery which has aim to discover process model. Nowadays, process mining become more popular in organization or company because by using its methods organization could easily capture information from each transaction happened [2].

Some previous research used program evaluation and review technique (PERT) [3] and goal programming [4] to optimize time and cost, where PERT is used to select optimal trace of the project and Goal Programming defined the goal itself. In this research, fuzzy miner approach will be used to extract process model with less structured processes [5]. Previously existing models tended to fail providing insightful models for less-structured processes, unlike the structured processes ones. It is known that in a less restrictive environment, the model will have more less-structured behavior and hard to understand. The goal of this fuzzy approach is to provide high-level view of the process, so that this method of process mining could emphasize more significant nodes. It could give a highlight on more important paths. As one of the youngest algorithms in process mining developed in 2007, fuzzy miner adapts better in less-structured environment, which traditional mining algorithms fail to.

Several algorithms have been used in business process discovery, such as time and control flow pattern [6] which enabling the process model to discover conditional-OR relationship. Corresponding research also has been done with time-based heuristic miner [7]. Another study conducted in Korea [8] has developed a fuzzy mining algorithm to determine an outpatient care process. This research was utilized for improvements from various sides. Therefore, this paper proposes a new improved fuzzy miner algorithm to represent binary correlation between activities. This new algorithm utilizes binary significance and binary correlation equally to acquire fuzzy model. While the original fuzzy miner algorithm uses various binary correlation metrics, the improved fuzzy miner algorithm uses only one metric and could capture the fuzzy model, accurately based on the event logs. Not only that reason, improved fuzzy miner algorithm was developed based on time interval in the threshold to capture more accurate business process model.

2. PRELIMINARY STUDY

2.1. Process mining and event log

Process mining is a process which combines process management and data science. This process has aims how to discover, monitor and improve the real processes by extracting the information from the event log [9]. There are many different algorithms that have been developed over years. These algorithms are based on either local approach (alpha algorithm and heuristic miner) or global approach (genetic miner and fuzzy miner) [10]. Each algorithm has different function and approach. Heuristic miner is a practical algorithm that can handle noise by using frequencies and parametrization [11], while a global approach algorithm such as genetic miner or fuzzy miner can mine complex logs [12]. The most recent issue is how the algorithm should be able to capture complex models or noisy logs, by using clustering and abstraction. Process mining stages adopted from Günther [13] explained in Figure 1. A recorded activity of a case within a timestamp and sometimes it has an originator (particular person who does the task) is a definition of an event log [14]. The record basically consists of date, time, user/actor, event ID or case ID, type, department, and source. Each activity has different attribute, depends on what the company need to record [15], [16].

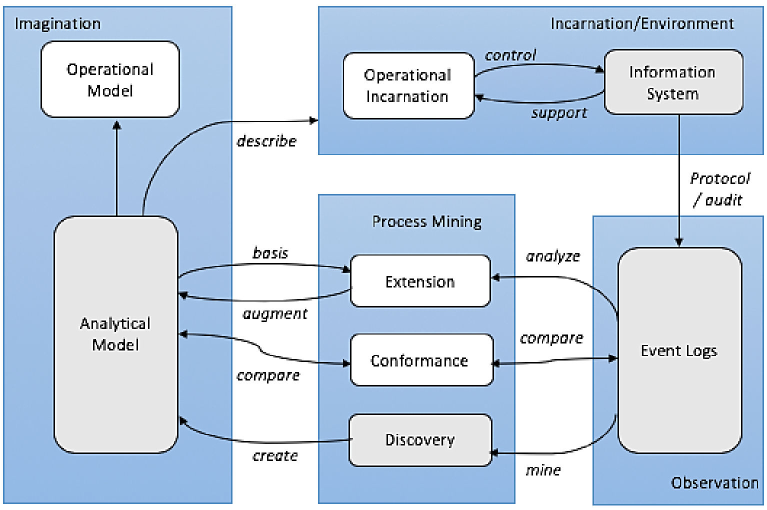

Figure 1. Process mining stages [5]

2.2. Fuzzy miner

Fuzzy miner algorithm was developed by Günther [5]. It is included in one of the youngest algorithms in process discovery compared to alpha miner and heuristics miner algorithm. The main advantage of this algorithm is it could directly tackle the problem of a large number of highly unstructured activities and behaviors. This method is used when the organization has complex and unstructured event log. It could also simplify the process model in an interactive way because it uses significance or correlation metrics [13]. Another interesting thing about this algorithm is it can prioritize the activities if there are too many of them. However, the shortcoming of the fuzzy model is it cannot be converted to any other type of process modeling language, but they can be used to animate event logs on top of a model built to sense dynamic process behavior. Although fuzzy is new to be used in business process discovery research, it has been widely used to solve problems such as synthesis of guaranteed stability regions of a nonstationary nonlinear system [17] and pavement performance evaluation [18].

2.3. Conformance checking

To validate the business process acquired from the process mining algorithm is called conformance checking [19], [20]. Conformance checking consists of four criterions, namely fitness, simplicity, precision, and generalization [20]. Process mining makes a conformance checking in order to proof that observed model is compatible with modeled process then extends to initial model [16].

- Fitness

Fitness is a value that shows the number of cases discovered in the process model [20]-[22]. Its value ranges from 0 to 1, where 0 means that there is no case discovered at all on the business process, while 1 means all the cases could be discovered by the algorithm and shown on the business process model. Fitness value (FV) could be measured by (1).

$$FV = \frac{\text{cases captured}}{\text{cases on actual event logs}} \tag{1}$$

- Simplicity

Simplicity is a value that shows of which a business process model has or does not have redundant activities [20], [23]. Simplicity value ranges from 0 to 1, where 0 means the business process model has much of redundant activities, while 1 means the business process model does not have any redundant activities. Simplicity value (SV) could be measured by (2).

$$SV = 1 - \frac{\text{duplicate activities + missing activities}}{\text{nodes on model}} \tag{2}$$

- Precision

Precision is a value that shows the accuracy of traces captured by the business process model [16], [20], [24]. Precision value ranges from 0 to 1, where 0 means there is no case captured from the event log by the algorithm, while 1 means all cases could be captured in the process model. Precision value (PV) is calculated by (3).

$$PV = 1 - \frac{\text{sum of bias traces}}{\text{traces from logs}} \tag{3}$$

- Generalization

Generalization is a value that shows flexibility of a business process model [20]. Generalization value ranges from 0 to 1, where 0 means the model shows specific form from the event logs, while 1 means it shows a more flexible form as a comparation from event logs discovery of nodes. Generalization value (GV) could be measured by (4).

$$GV = 1 - \frac{\sum_{1}^{\#modelnode}(\sqrt{\#actualnode})1^{-1}}{\#modelnode} \tag{4}$$

3. RESEARCH METHOD

In this research, the proposed method consists of steps on how improved time-based fuzzy miner worked. Improved fuzzy miner algorithm is used to model business process from the event logs, and then compared to fuzzy model from ProM software. Both models will later be compared and evaluated in a term of conformance checking, to determine which model results better. Proposed method explained in Figure 2.

Figure 2. Proposed method

3.1. Collecting event logs

In this study, event logs were collected from RMA business process in a wireless distribution company, Surabaya, Indonesia. Event logs were generated from 22 data (which further will be acknowledged as case), consisting of activity, start timestamp, and complete timestamp. Activity means the event or business process executed in the company, meanwhile start and complete timestamp are related to execution time of each activity.

3.2. Process discovery using original fuzzy miner

Fuzzy miner is applied to extract business process model from the event logs. Fuzzy model is based on event logs extraction using the original ProM fuzzy miner algorithm. This model is based on 0.5 utilization ratio, which means this model considers significance and correlation equally. The use of fuzzy miner features aggregation and abstraction [5], [25], where it enables the analyst to highlight particular subset of activities. Aggregation is used for clustering coherent, less significant structures. Aggregation is used to simplify the model. Meanwhile, abstraction is used to remove isolated, less significant structures. This is done in purpose to remove detached nodes which doesn’t contribute significantly to the model, so that the model will be simplified.

Simplification from the log events could be approached by an adaptive simplification framework [14]. This approach is based on configurable framework to measure significance and correlation. The measurement is done through three primary types of metrics: unary significance, binary significance, and binary correlation. Each metric could be built directly from the log and will later be used to develop and visualize fuzzy model.

Unary significance is measured by three metrics: frequency significance, routing significance, and importance significance. Later, those values will be aggregated into aggregated unary significance. Binary significance is measured by two metrics, frequency significance and distance significance. Binary correlation is measured by proximity correlation, originator correlation, endpoint correlation, data type correlation, and data value correlation. The output of this step is an extracted business process model from the input of event logs. The mining process is performed with the help of ProM software, using fuzzy miner.

3.3. Modified time-based fuzzy miner

Fuzzy miner is used to extract business process model from the event logs. The output from fuzzy process mining is a fuzzy model to accommodate business process model in a less-structured environment. The proposed modified time-based fuzzy miner considers double timestamp on occurring activities to determine their binary correlation. This correlation could be used as the decision of parallel activities (captured as AND-split or XOR-split). Where the original fuzzy miner uses proximity correlation, originator correlation, endpoint correlation, data type correlation, and data value correlation to evaluate correlated event classes that occur one after another, this rule could accommodate event classes that occur simultaneously based on their interval from most recent preceding activity ending timestamp and current activity starting timestamp. Interval significance assigns the value of significance=1 to the relation with smallest mean interval. The other relation interval significant could be measured in relative to the smallest interval, which explained by (5).

$$Int.Sig. = \frac{1}{relation\ interval - least\ occuring\ interval} \tag{5}$$

Fundamental metrics to decide on abstraction or aggregation are significance and correlation metrics. The options are preserving every highly significant behavior and omitting less significant and less correlated behavior.

3.4. Conformance checking evaluation

The final step of this research is to evaluate business process model captured from both algorithms. This evaluation is done through the measurement of conformance checking. Conformance checking evaluation consists of fitness value, precision value, simplicity value, and generalization value by using (1)-(4).

4. RESULTS AND ANALYSIS

The results of research using improved fuzzy miner were explained in this section. Event logs used in this research are shown in Table 1. Event logs consist of number of cases, name of activity, start timestamp, and complete timestamp. Based on data presented in Table 1, we know that standard operating procedure (SOP) begins with activity RMA request from customer and ends with Creating delivery order. Based on event logs from Table 1, we developed the business process of RMA as shown in Figure 3.

The implementation of this research was started by using ProM software. Firstly, the same event logs from Table 1 were used and secondly, they were processed directly by ProM 6.9 with fuzzy miner algorithm. The results of business process model presented in Figure 4. The same way was applied for improved fuzzy algorithm. Event logs in Table 1 were run and business process model was generated by using our system which shown in Figure 5 (see Appendix). Based on Figure 4 and Figure 5 we can conclude that our proposed algorithm does not contain loop and executed sequentially.

Table 1. Part of event logs from RMA business process in a wireless distribution company

Case	Activity	Start Timestamp	Complete Timestamp	Case	Activity	Start Timestamp	Complete Timestamp
1	Request RMA from Customer	1/31/18 8:00 AM	1/31/18 8:04 AM	2	Request RMA from Customer	1/31/18 9:00 AM	1/31/18 9:06 AM
1	Device status checking	1/31/18 8:04 AM	1/31/18 8:06 AM	2	Device status checking	1/31/18 9:06 AM	1/31/18 9:08 AM
1	Warranty status info	1/31/18 8:06 AM	1/31/18 8:10 AM	2	Warranty status info	1/31/18 9:08 AM	1/31/18 9:12 AM
1	Creating service receipt	1/31/18 8:10 AM	1/31/18 8:18 AM	2	Creating service receipt	1/31/18 9:12 AM	1/31/18 9:17 AM
1	Creating RMA registration form	1/31/18 8:18 AM	1/31/18 8:23 AM	2	Creating RMA registration form	1/31/18 9:17 AM	1/31/18 9:20 AM
1	Submit device to technician	1/31/18 8:23 AM	1/31/18 8:30 AM	2	Submit device to technician	1/31/18 9:20 AM	1/31/18 9:28 AM
1	Service	1/31/18 8:30 AM	1/31/18 10:30 AM	2	Service	1/31/18 9:28 AM	1/31/18 1:28 PM
1	Checking service result	1/31/18 10:30 AM	1/31/18 10:35 AM	2	Checking service result	1/31/18 1:28 PM	1/31/18 1:40 PM
1	Calculating charge	1/31/18 10:40 AM	1/31/18 11:00 AM	2	Calculating charge	1/31/18 1:40 PM	1/31/18 1:45 PM
1	Creating service quotation	1/31/18 11:00 AM	1/31/18 11:13 AM	2	Creating delivery order	1/31/18 1:45 PM	1/31/18 1:50 PM
1	Creating bill	1/31/18 11:13 AM	1/31/18 11:30 AM				
1	Creating delivery order	1/31/18 11:13 AM	1/31/18 11:20 AM				

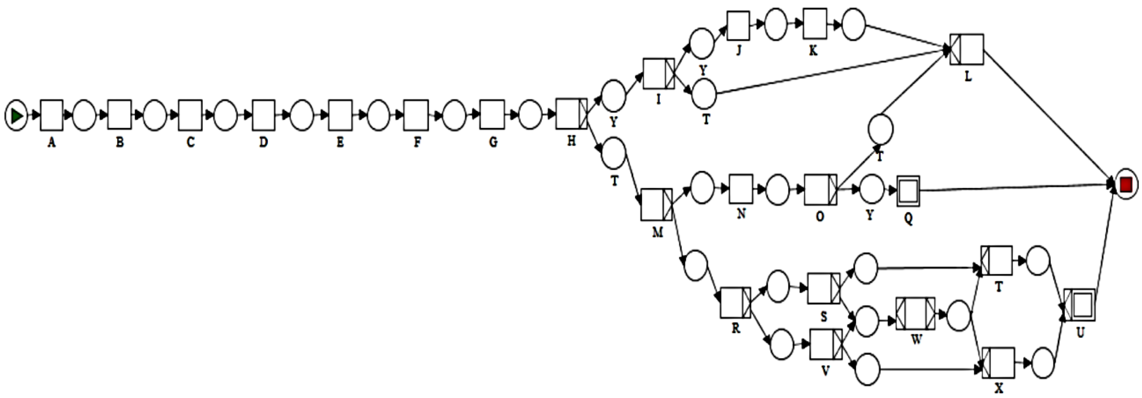

Figure 3. Business process model of RMA

Table 2 and Table 3 explain the proposed modified time-based fuzzy miner considering double timestamp on occurring activities to determine their binary correlation. Table 2 presents example of double timestamp event log, meanwhile Table 3 is about time interval significance. Based on Table 2, we get the information that activity A, B, C, D are executed for about 2, 4, 4, 4 minutes respectively. On the other hand, from Table 3, the data explained that activity B is processed directly without time interval after activity A is done, different with activity B to C and activity C to D which have time interval. This also applies to significance of activity A, B, C, D.

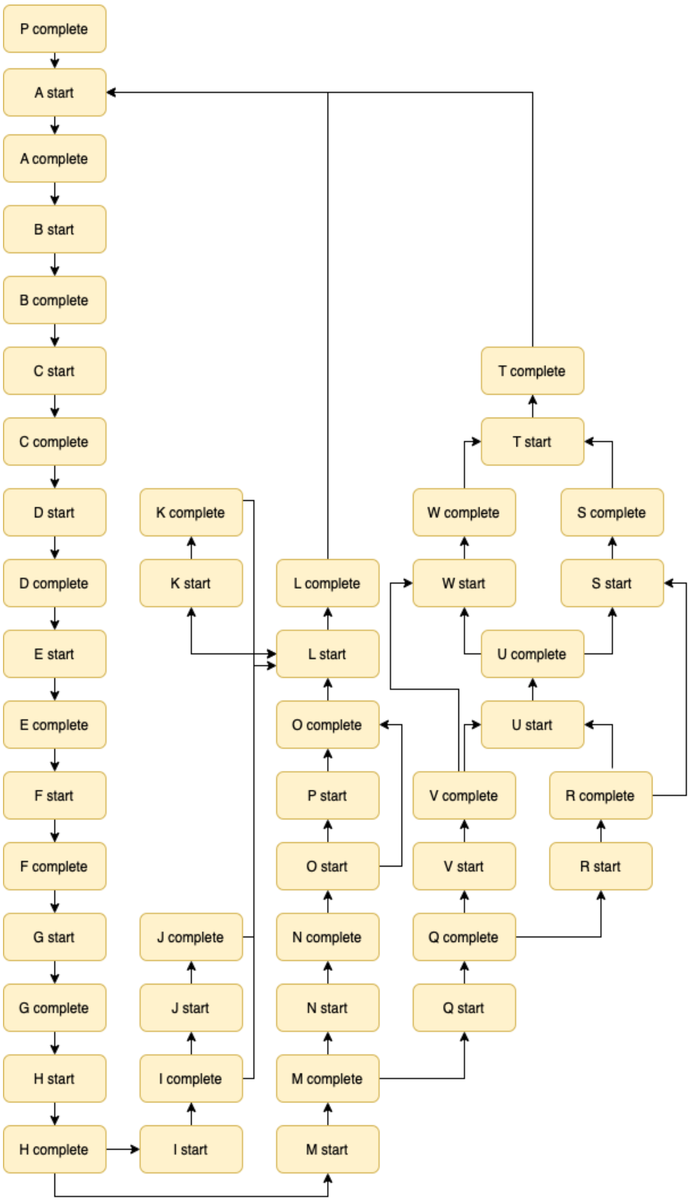

Figure 4. Original fuzzy model

Table 2. Example of double timestamp log

Activity	Start Timestamp	Complete Timestamp
A	8:00	8:02
B	8:02	8:06
C	8:08	8:12
D	8:16	8:20

Table 3. Time interval significance

Preceding Relation	A⇒B	B⇒C	C⇒D
Interval	0	2	4
Significance	1.00	0.50	0.25

The calculation results for each metric could be seen on Table 4. We use (5) to do interval significance. Table 5 (see Appendix) explains the decision for each relation of activity based on binary significance and correlation whether they are preserved or omitted in a new business process model of a company. After the implementation was done, the final step in our research is conformace checking evaluation. This step is important to know that our proposed method provides better result than that of original fuzzy miner. We use (1), (2), (3), (4) to calculate fitness value, simplicity, precision, and generalization value from both algorithms.

The results of the conformance checking are described in Table 6. The modified time-based fuzzy miner algorithm shows that the conformance checking value are better than the original fuzzy miner processed using ProM software. This is caused by the modification on binary correlation between activities, which takes time interval from complete timestamp and start timestamp into account. Specifically, based on Table 6, we can conclude that our improved fuzzy miner algorithm has higher precision value and generalization value than that of original fuzzy miner meanwhile fitness value and simplicity value are still the same.

Table 4. Binary frequency significance

#	Relation	Frequency	Binary Significance	#	Relation	Frequency	Binary Significance
1	A⇒B	22	1.00	15	N⇒O	3	0.14
2	B⇒C	22	1.00	16	O⇒P	1	0.05
3	C⇒D	22	1.00	17	O⇒L	2	0.09
4	D⇒E	22	1.00	18	M⇒Q	12	0.55
5	E⇒F	22	1.00	19	Q⇒R	6	0.27
6	F⇒G	22	1.00	20	R⇒S	3	0.14
7	G⇒H	22	1.00	21	S⇒T	6	0.27
8	H⇒I	6	0.27	22	R⇒U	2	0.09
9	I⇒J	2	0.09	23	U⇒S	4	0.18
10	J⇒K	2	0.09	24	Q⇒V	6	0.27
11	K⇒L	3	0.14	25	V⇒U	3	0.14
12	I⇒L	4	0.18	26	V⇒W	3	0.14
13	H⇒M	15	0.68	27	U⇒W	3	0.14
14	M⇒N	3	0.14	28	W⇒T	6	0.27

Table 6. Conformance checking evaluation

Algorithms	Conformance Checking Evaluation			
	Fitness	Precision	Simplicity	Generalization
Original Fuzzy Miner	1.00	0.82	1.00	0.92
Modified Time-based Fuzzy Miner	1.00	1.00	1.00	0.94

5. CONCLUSION

This research proposes a modification of fuzzy miner algorithm considering time interval to represent binary correlation between activities. This improved algorithm utilizes binary significance and binary correlation equally to acquire fuzzy model to model business process. While the original fuzzy miner algorithm uses various binary correlation metrics, the improved fuzzy miner algorithm uses only one metric and could capture the fuzzy model, accurately based on the event logs.

To prove our proposed algorithm worked, a comparison between original fuzzy miner which modeled with ProM software and time-based fuzzy miner algorithm were done. The results showed that the improved algorithm has higher value on conformance checking and able to capture business process model based on time interval, by using only time-interval significance as a binary correlation metrics. This also stated that the proposed algorithm could depict the traces in the business process precisely. The limitation of this study is that the proposed method is only able to generate business process model well without knowing those are XOR, OR, AND parallel in terms of parallel relation. In order to overcome this limitation, we are planning to create some thresholds like modified alpha miner and modified heuristics miner algorithm did.

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APPENDIX

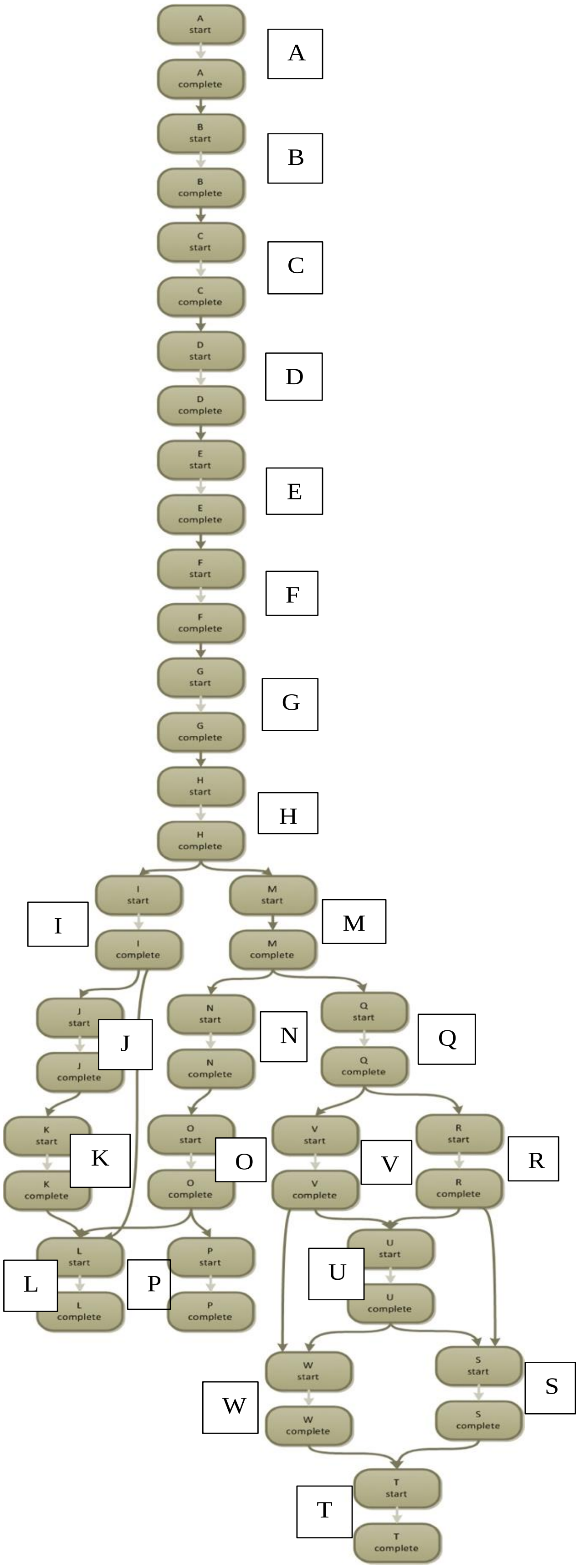

Figure 5. Modified fuzzy model

Table 5. Results for binary significance and correlation

#	Activity	Significance	Correlation	Decision	#	Activity	Significance	Correlation	Decision
1	A start ⇒ A complete	1	0.25	Preserved	28	E complete ⇒ F start	1	1.00	Preserved
2	B start ⇒ B complete	1	0.50	Preserved	29	F complete ⇒ G start	1	1.00	Preserved
3	C start ⇒ C complete	1	0.25	Preserved	30	G complete ⇒ H start	1	1.00	Preserved
4	D start ⇒ D complete	1	0.13	Preserved	31	H complete ⇒ I start	0.27	1.00	Preserved
5	E start ⇒ E complete	1	0.10	Preserved	32	I complete ⇒ J start	0.09	1.00	Preserved
6	F start ⇒ F complete	1	0.10	Preserved	33	J complete ⇒ K start	0.09	1.00	Preserved
7	G start ⇒ G complete	1	0.01	Preserved	34	K complete ⇒ L start	0.14	1.00	Preserved
8	H start ⇒ H complete	1	0.10	Preserved	35	I complete ⇒ L start	0.18	1.00	Preserved
9	I start ⇒ I complete	1	0.05	Preserved	36	H complete ⇒ M start	0.68	1.00	Preserved
10	J start ⇒ J complete	1	0.05	Preserved	37	M complete ⇒ N start	0.14	1.00	Preserved
11	K start ⇒ K complete	1	0.05	Preserved	38	N complete ⇒ O start	0.14	1.00	Preserved
12	L start ⇒ L complete	1	0.03	Preserved	39	O complete ⇒ P start	0.05	1.00	Preserved
13	M start ⇒ M complete	1	0.10	Preserved	40	O complete ⇒ L start	0.09	1.00	Preserved
14	N start ⇒ N complete	1	0.07	Preserved	41	M complete ⇒ Q start	0.55	1.00	Preserved
15	O start ⇒ O complete	1	0.07	Preserved	42	Q complete ⇒ R start	0.27	1.00	Preserved
16	P start ⇒ P complete	1	0.02	Preserved	43	R complete ⇒ S start	0.14	1.00	Preserved
17	Q start ⇒ Q complete	1	0.02	Preserved	44	S complete ⇒ T start	0.27	1.00	Preserved
18	R start ⇒ R complete	1	0.07	Preserved	45	R complete ⇒ U start	0.09	1.00	Preserved
19	S start ⇒ S complete	1	0.10	Preserved	46	U complete ⇒ S start	0.18	1.00	Preserved
20	T start ⇒ T complete	1	0.10	Preserved	47	Q complete ⇒ V start	0.27	1.00	Preserved
21	U start ⇒ U complete	1	0.03	Preserved	48	V complete ⇒ U start	0.14	1.00	Preserved
22	V start ⇒ V complete	1	0.05	Preserved	49	V complete ⇒ W start	0.14	1.00	Preserved
23	W start ⇒ W complete	1	0.10	Preserved	50	U complete ⇒ W start	0.14	1.00	Preserved
24	A complete ⇒ B start	1	1.00	Preserved	51	W complete ⇒ T start	0.27	1.00	Preserved
25	B complete ⇒ C start	1	1.00	Preserved	52	L complete ⇒ A start	0.41	0.00	Omitted
26	C complete ⇒ D start	1	1.00	Preserved	53	P complete ⇒ A start	0.05	0.00	Omitted
27	D complete ⇒ E start	1	1.00	Preserved	54	T complete ⇒ A start	0.55	0.00	Omitted

REFERENCES

[1] G. I. Budiawati and R. Sarno, "Time and cost optimization of business process RMA using PERT and goal programming," *TELKOMNIKA Telecommunication, Computing, Electronics and Control*, vol. 17, no. 2, pp.781-787, April 2019, doi: 10.12928/telkomnika.v17i2.11792.

[2] W. M. P. van der Aalst, H. T. de Beer, and B. F. van Dongen, "Process mining and verification of properties: An approach based on temporal logic," *Lecture Notes in Computer Science, Springer,* vol. 3760, pp. 130-147, 2010, doi: 10.1007/11575771_11.

[3] Y. Mei, Y. Jiawei, and Z. Zhigang, "A computing model: the closed-loop optimal control for large-scale one-of-a-kind production based on multilevel hierarchical PERT-Petri net," *IEEE Technology and Engineering Management Conference (TEMSCON)*, 2018, doi: 10.1109/TEMSCON.2018.8488428.

[4] M. A. P. Subali, R. Sarno, and Y. A. Effendi, "Time and cost optimization using fuzzy goal programming," *International Conference on Information and Communications Technology (ICOIACT),* 2018, pp. 471-476, doi: 10.1109/ICOIACT.2018.8350723.

[5] C. W. Günther and W. M. P. van der Aalst, "Fuzzy Mining–Adaptive Process Simplification Based on Multi-perspective Metrics," *Lecture Notes in Computer Science, Springer,* vol. 4714, pp. 328-343, 2007, doi: 10.1007/978-3-540-75183-0_24.

[6] Y. A. Effendi and R. Sarno, "Time-based α+ miner for modelling business processes using temporal pattern," *TELKOMNIKA Telecommunication Computing Electronics and Control,* vol. 18 no. 1, pp. 114-123, February 2020, doi: 10.12928/telkomnika.v18i1.12733.

[7] Y. A. Effendi, F. Retrialisca, and N. Nuzulita, "Conformance Checking to Evaluate Business Process Models using Modified Time-based Heuristics Miner Algorithm," *IEEE Conference on Sustainable Utilization and Development in Engineering and Technologies*, 2019, pp. 81-86, doi: 10.1109/CSUDET47057.2019.9214767.

[8] E. Kim *et al.*, "Discovery of outpatient care process of a tertiary university hospital using process mining," *Healthcare informatics research*, vol. 19, no. 1, pp. 42–49, 2013, doi: 10.4258/hir.2013.19.1.42.

[9] A. Cecconi, G. D. Giacomo, C. D. Ciccio, F. M. Maggi, and J. Mendling, "A Temporal Logic-Based Measurement Framework for Process Mining," *2nd International Conference on Process Mining (ICPM),* 2020, pp. 113-120, doi: 10.1109/ICPM49681.2020.00026.

[10] E. P. Gupta, "Process Mining A Comparative Study," *International Journal of Advanced Research in Computer and Communication Engineering*, vol. 3, no 11, pp. 8594-8598, November 2014, doi: 10.17148/IJARCCE.2014.31154.

[11] A. P. Kurniati, G. Kusuma, and G. Wisudiawan, "Implementing heuristic miner for different types of event logs," *International Journal of Applied Engineering Research,* vol. 11, no. 8, pp 5523-5529, 2016.

[12] S. Goedertier, J. de Weerdt, D. Martens, J. Vanthienen, and B. Baesens, "Process discovery in event logs: An application in the telecom industry," *Applied Soft Computing Journal,* vol. 11, no. 2, pp. 1697-1710, 2011, doi: 10.1016/j.asoc.2010.04.025.

[13] C. W. Günther, "Process mining in flexible environments," Computer Science, Technische Universiteit Eindhoven, 2009, doi: 10.6100/IR644335.

[14] S. Al-Fedaghi and F. Mahdi, "Events Classification in Log Audit," *International Journal of Network Security & Its Applications (IJNSA)*, vol. 2, no. 2, pp. 58-73, April 2010, doi: 10.5121/ijnsa.2010.2205.

[15] W. M. P. van der Aalst *et al.*, "Business process mining : an industrial application," *Information Systems*, vol. 32, no. 5, pp. 713-732, 2007, doi: 10.1016/j.is.2006.05.003.

[16] J. Xia, "Automatic determination of graph simplification parameter values for fuzzy miner," *Mathematics and Computer Science*, 2010.

[17] V. Berdnikov and V. Lokhin, "Synthesis of Guaranteed Stability Regions of a Nonstationary Nonlinear System with a Fuzzy Controller," *Civil Engineering Journal*, vol. 5, no. 1, pp. 107-116, January 2019, doi: 10.28991/cej-2019-03091229.

[18] S. Wadalkar, R. K. Lad, and R. K. Jain, "Performance Assessment of Flexible Pavements: Fuzzy Evidence Theory Approach," *Civil Engineering Journal,* vol. 6, no. 8, pp. 1492-1502, August 2020, doi: 10.28991/cej-2020-03091562.

[19] J. Potavin, N. Jongswat, and W. Premchaiswadi, "Applying Fuzzy-Genetic mining in conformance and dependency relations," *Tenth International Conference on ICT and Knowledge Engineering*, 2012, pp. 228-235, doi: 10.1109/ICTKE.2012.6408560.

[20] Y. A. Effendi and F. Retrialisca, "Transforming Timestamp of a CSV Database to an Event Log," *8th International Conference on Computer and Communication Engineering (ICCCE),* 2021, pp. 367-372, doi: 10.1109/ICCCE50029.2021.9467226.

[21] J. de Weerdt, M. de Backer, J. Vanthienen, and B. Baesens, "A robust F-measure for evaluating discovered process models," *IEEE Symposium on Computational Intelligence and Data Mining (CIDM),* 2011, pp. 148-155, doi: 10.1109/CIDM.2011.5949428.

[22] W. M. P. van der Aalst, "Process mining: discovery, conformance and enhancement of business processes," *Springer*, 2011, doi: 10.1007/978-3-642-19345-3.

[23] A. Burattin, F. M. Maggi, and A. Sperduti, "Conformance checking based on multi-perspective declarative process models," *Expert Syst. Appl.*, vol. 65, pp. 194-211, 2016, doi: 10.1016/j.eswa.2016.08.040.

[24] V. Naderifar, S. Sahran, and Z. Shukur, "A Review on Conformance Checking Technique for the Evaluation of Process Mining Algorithms," *TEM Journal,* vol. 8, no. 4, pp. 1232-1241, November 2019, doi: 10.18421/TEM84-18.

[25] W. Premchaiswadi, P. Porouhan, and N. Premchaiswadi, "Process Modeling, Behavior Analytics and Group Performance Assessment of e-Learning Logs Via Fuzzy Miner Algorithm," *IEEE 42nd Annual Computer Software and Applications Conference (COMPSAC),* 2018, pp. 304-309, doi: 10.1109/COMPSAC.2018.10247.