Int j simul model 23 (2024) 1, 17-28
Original scientific paper

SIMULATIONS TO PREDICT PROCESS MODEL ALIGNMENT WITH STANDARD OPERATING PROCEDURE

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Abstract
The absence of a Standard Operating Procedure (SOP) can lead to many problems in operations within organisations. Process mining techniques can discover process models that reflect the actual behaviour of the process implementations by using event logs extracted from information systems. However, the process models discovered by process mining often have too many variations and deviations when compared to the actual SOPs of the processes. This study attempted to compare three prediction methods in finding a process model from process mining that has the closest properties to the actual SOP. The compared methods are Receiver Operating Characteristics (ROC), the four quality dimensions, and similarity measures for structural and behavioural similarities. For the experiment, we designed a synthetic SOP that served as a ground truth for evaluating the performance of the three prediction methods in this study. We used a synthetic event log extracted from a dummy information system we particularly built for this study to test the methods. This study's results can be useful, e.g. for auditors to save a lot of time from conducting extensive surveys when SOPs are not readily available.
(Received in May 2023, accepted in November 2023. This paper was with the authors 2 months for 2 revisions.)

Key Words: Standard Operating Procedure, Behavioural Similarity, Four Quality Dimensions, Receiver Operating Characteristic, Structural Similarity

1. INTRODUCTION

One of the reasons for organisations to automate business processes is to improve the process efficiency of activities. However, implementations of information systems often cause problems such as lack of knowledge among users, resulting in failures to complete processes, unclear procedures, lack of accountability, and, to some extent, abuse of the system that leads to fraud cases [1-3]. Such problems can be attributed to many causing factors. From our perspective, one of the factors is the absence of guidance on how, who, where, or when to use the systems in question properly. This guidance is often referred to as Standard Operating Procedure (SOP). Bodur (2018) defined SOP as "a written set of rules that specify in advance and detail how an organisation is set up to perform a specific job, how it will function in an effective, harmonious and conclusive manner, and who, where, when, and what needs to be done. It also includes information on how to share, what to record, who to report and when to report." [4] In practice, SOPs in organisations mostly focus on the how, what, and who aspects of the definition.

In cases where SOPs are not available as references, process mining is often used to address the problem and monitor the processes. Process mining is a discipline that focuses on generating process models by analysing event logs extracted from information systems. Process models generated from process mining activities, however, generally only exhibit chains of events depicting how the processes are executed in the systems. The generated models from the

activities can sometimes be over-fitting or under-fitting, so they are not the most suitable models for formal guidance. References on how the processes should be completed are essentially needed to measure conformance within an organisation [1, 5, 6].

While many researchers focus on using mathematical modelling for making simulations, such as in [7], some focus on using machine learning methods to mine data, such as in [8, 9]. Some other researchers have focused on evaluating the metrics of models similarity measures to compare the similarity distances between models, such as discussed in [10, 11], from which some of our arguments in this study are based. From the many available methods for measuring model similarity, quite a few studies focused on using structural similarity measures, such as discussed in [12]. In contrast, many other studies focused on using behavioural similarity measures, such as those discussed in [13, 14], on which we also based some of our arguments in this study. Despite many other methods proposed by researchers, such as the weighted graph model [15] or weighted tree declarative pattern model [16], we use the combination of structural and behavioural metrics to measure the similarities between models used in this study.

In spite of SOP analysis in various fields of studies and the four quality dimensions of process mining are well-researched topics, such as discussed in [17, 18], researches that use both methods while also incorporating similarity measures are quite scarce.

2. METHODS

2.1 Synthetic SOP, event logs, and thresholds

The data set we used in this study is a synthetic event log generated from a dummy information system we created on ProcessMaker™ by following a previously designed synthetic SOP. The synthetic SOP was intended as a ground truth, as the name suggests, for measuring the predictive performance of each method we used in this study. The synthetic SOP used in this study was intentionally designed as simple as possible to avoid too many discovery variations that would distort the predictive properties of the methods being compared in this study. Fig. 1 illustrates the synthetic SOP we used in this study.

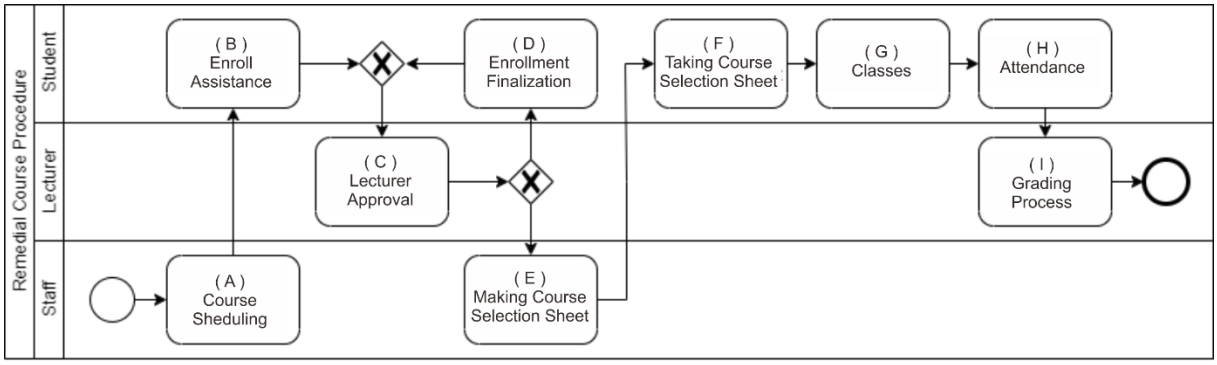

Figure 1: Synthetic SOP used for simulation in this study.

Different users then simulated the created system according to the number of roles in the systems (and the synthetic SOP). We took 104 simulations to generate an event log containing 15 traces of different scenarios of conformance and non-conformance to the SOP (see Table I).

Determining thresholds for information mining, including process mining, is challenging as there aren't criteria for it [19]. In this study, we mapped each Case ID from the event log in a scatter plot based on the number of activities in each case. Then, we put thresholds accordingly (see Fig. 2). We marked the conformance cases with green circles and the non-conformance cases with red triangles in order to easily measure the accuracy rate of the methods we used in this study.

Table I: Synthetic event log scenarios.

Freq.	Ref.	Trace	*PT*
68	σ1	{*A, B, C, E, F, G, H, I*}	0.5
8	σ2	{*A, B, C, D, C, E, F, G, H, I*}	0.6
6	σ3	{*A, B, C, E, F, G, H*}	0.4
5	σ4	{*A, B, C, E, F*}	0.2
3	σ5	{*A, B, C, D, C*}	0.2
3	σ6	{*A, B, C, E, F, G*}	0.3
2	σ7	{*A, B, C*}	0.1
2	σ8	{*A, B, C, D, C, D, C*}	0.4
1	σ9	{*A, B, C, E*}	0.2
1	σ10	{*A, B, C, D, C, D, C, D, C*}	0.5
1	σ11	{*A, B, C, D, C, E, F, G, H*}	0.5
1	σ12	{*A, B, C, D, C, D, C, E, F*}	0.5
1	σ13	{*A, B, C, D, C, D, C, E, F, G, H, I*}	0.7
1	σ14	{*A, B, C, D, C, D, C, D, C, D, C, E, F*}	0.8
1	σ15	{*A, B, C, D, C, D, C, D, C, E, F, G, H, I*}	0.9

A = course scheduling, *B* = enrol assistance, *C* = lecturer approval, *D* = enrolment finalization, *E* = making course selection sheet, *F* = taking course selection sheet, *G* = classes, *H* = attendance, *I* = grading process, *PT* = position in threshold.

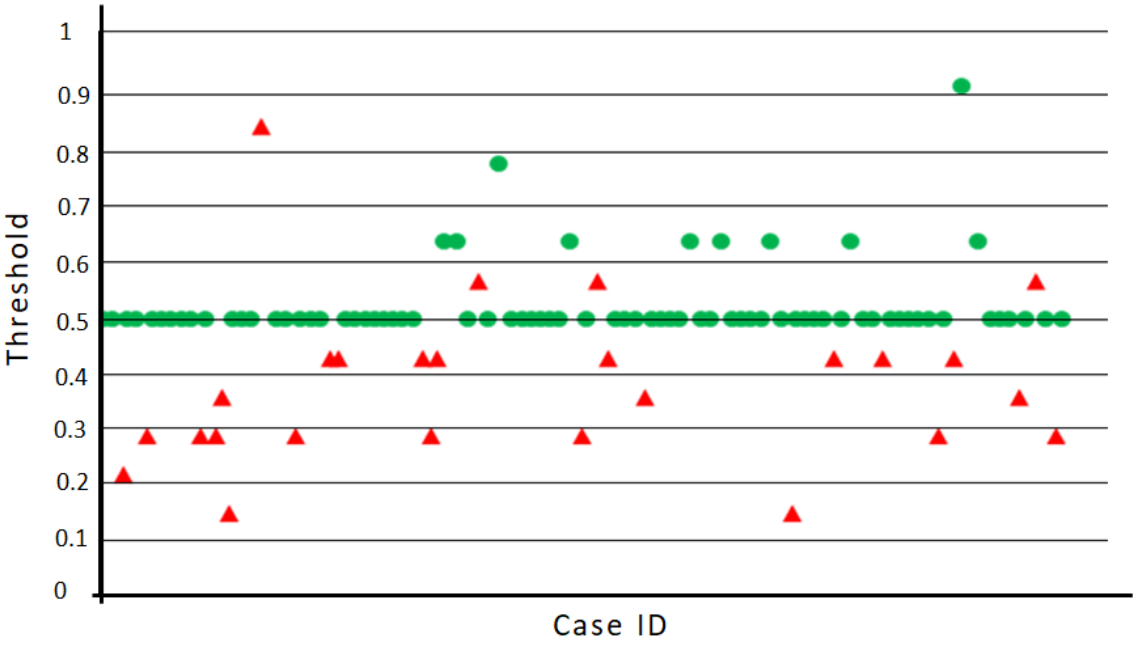

Figure 2: Case IDs from our synthetic event log scattered in threshold 0-1 where a green circle indicates conformance and a red triangle indicates non-conformance.

From this point, our approach was split into two directions. In one direction of the two, we analysed the traces using Receiver Operating Characteristics (ROC). In the other direction, we used the event log to discover process models representing every threshold in the scatter plot.

2.2 Receiver Operating Characteristics (ROC) analysis

We used the standard Receiver Operating Characteristic (ROC) practice of using confusion matrices to measure true positive (*TP*), false positive (*FP*), true negative (*TN*), and false negative (*FN*) for each threshold (*T*) in the plot. The results from our calculations were then used to discover the values of true positive rate (*TPR*), false positive rate (*FPR*), true negative rate (*TNR*), and false negative rate (*FNR*) for each threshold setting. Next, we plotted the *TPR*

against *FNR* to create the ROC curve for determining the best predictive model. As in standard practice, we aimed to locate the classifier that is closest to (0.1) and the furthest from *TPR = FPR*. A more detailed explanation of ROC is discussed in [20].

In this study, we used the following formulas to conduct our ROC analysis.

$$TPR = \frac{TP}{P} = \frac{TP}{TP+FN} = 1 - FNR \quad (1)$$

$$TNR = \frac{TN}{N} = \frac{TN}{TN+FP} = 1 - FPR \quad (2)$$

$$FPR = \frac{FP}{N} = \frac{FP}{FP+TN} = 1 - TNR \quad (3)$$

$$FNR = \frac{FN}{P} = \frac{FN}{FN+TP} = 1 - TPR \quad (4)$$

$$ACC = \frac{TP+TN}{P+N} = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

where *P* is condition positive, *N* is condition negative, and *ACC* is accuracy.

After the event log was mapped into an ROC plot with threshold settings of 0-1, we performed the ROC measurement. Table II describes the results of our measurement.

Table II: Prediction model.

T	***TP***	***FP***	***TN***	***FN***	***TPR***	***FPR***	***TNR***	***FNR***	***ACC***
0	78	26	0	0	1.00	1.00	0.00	0.00	0.75
0.1	78	26	0	0	1.00	1.00	0.00	0.00	0.75
0.2	78	24	2	0	1.00	0.92	0.08	0.00	0.77
0.3	78	15	11	0	1.00	0.58	0.42	0.00	0.86
0.4	78	12	14	0	1.00	0.46	0.54	0.00	0.88
0.5	78	4	22	0	1.00	0.15	0.85	0.00	0.96
0.6	10	1	25	68	0.13	0.04	0.96	0.87	0.34
0.7	2	1	25	76	0.03	0.04	0.96	0.97	0.26
0.8	1	1	25	77	0.01	0.04	0.96	0.99	0.25
0.9	1	0	26	77	0.01	0.00	1.00	0.99	0.26
1	0	0	26	78	0.00	0.00	1.00	0.00	0.25

We then made an ROC curve to determine the best threshold (see Fig. 3). From the ROC analysis perspective, threshold 0.5 had the best prediction model of all the threshold settings. This finding is consistent with what is expected from the mapping in Fig. 2.

2.3 Process models discovery

In the other direction of this stage, we generated process models from the event log that represent each threshold in the plot. We used the Inductive Miner (IM) algorithm, which was readily available as a plug-in on ProM™ 6, to discover the process models. IM is a discovery technique to create a process tree for a given event log and works by repeatedly finding branches in the process tree. This algorithm has benefits such as soundness and block-structuredness of the discovered process models. Specifically, we used Infrequent Inductive Miner (IIM), a variant of the Inductive Miner algorithm, to enable us to set various thresholds in process discovery for simulations in this paper. The structure and methodology of the IM algorithm are well-explained in [21-25].

Using the IIM algorithm, some threshold settings discovered the same process models. These process models were the inputs for performing both quality dimensions and similarity measures. Figs. 4 to 8 illustrates the process models discovered by the IM algorithm for threshold settings of 0-1.

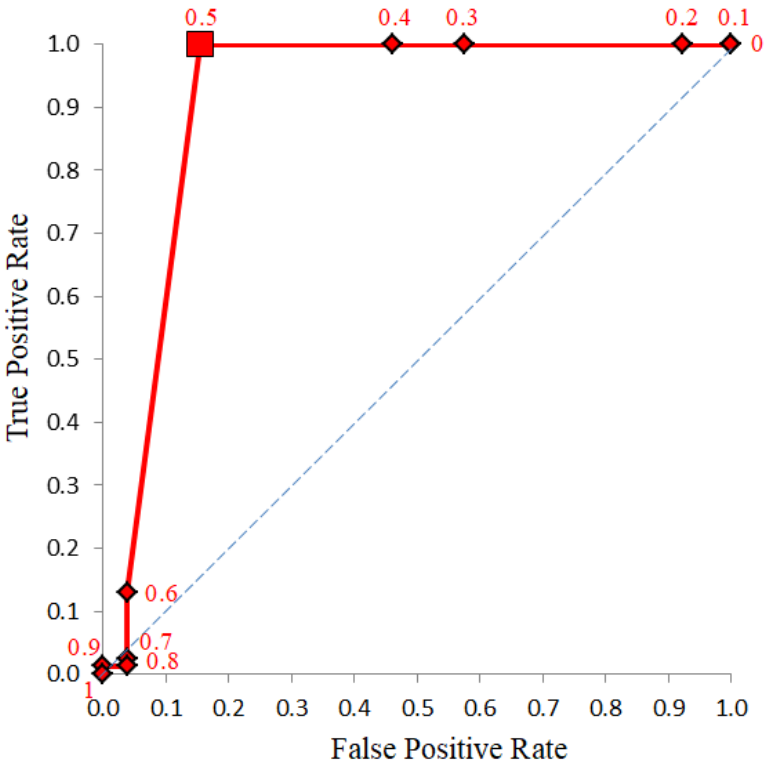

Figure 3: ROC curve of the prediction models where red points indicate positions in the threshold.

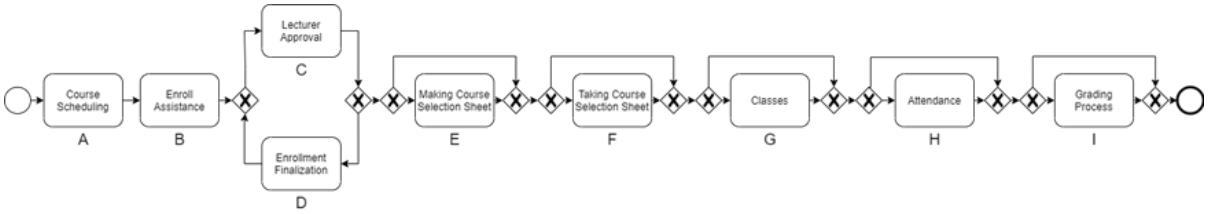

Figure 4: Discovered process models using threshold settings of 0, 0.1, and 0.2.

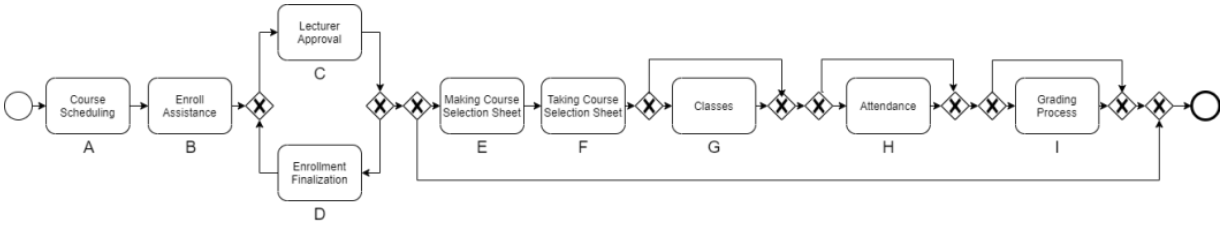

Figure 5: Discovered process models using threshold settings of 0.3.

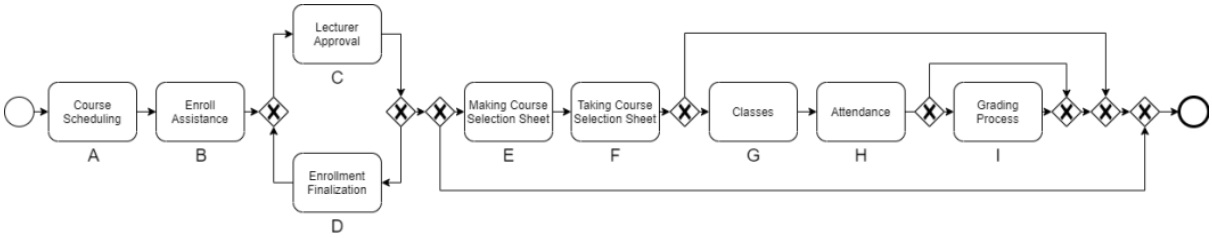

Figure 6: Discovered process models using threshold settings of 0.4 and 0.5.

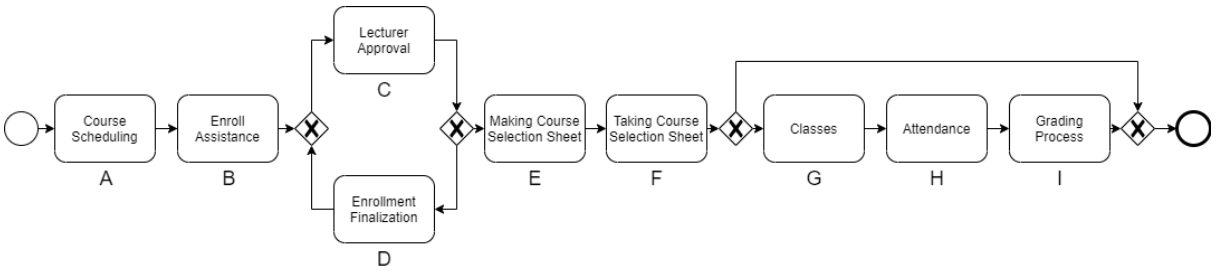

Figure 7: Discovered process models using threshold settings of 0.7 and 0.8.

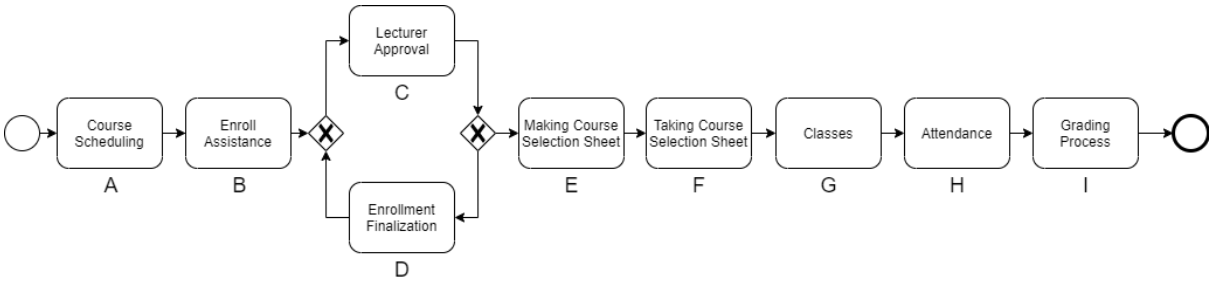

Figure 8: Discovered process models using threshold settings of 0.9.

2.4 Four quality dimensions measures

At this phase, we calculated the quality of the process models that were discovered from the previous stage, representing all thresholds. The criteria we measured were fitness, precision, generalisation, and simplicity. In performing our calculations, we used the same techniques and formulas that are proposed in [15, 26-28].

We used the following formula to measure the fitness (*F*), precision (*P*), generalisation (*G*), and simplicity (*S*) of our process models.

$$F = \frac{1}{2}\left(1 - \frac{m}{c}\right) + \frac{1}{2}\left(1 - \frac{r}{p}\right) \tag{6}$$

where *p* is produced activities in process models, *c* is consumed activities, *m* is missing activities, and *r* is remaining activities.

$$P = 1 - \frac{\sum v^{nv \cdot \frac{\#oe - \#ue}{oe}}}{tv} \tag{7}$$

where *v* is visited activities, *nv* is the number of visits, *#oe* is the number of outgoing edges, *#ue* is the number of used edges, *oe* is outgoing edges, and *tv* is total visits overall activities.

$$G = 1 - \frac{\sum d\left(\sqrt{\#e}\right)^{-1}}{dt} \tag{8}$$

where *d* is nodes, *#e* is the number of executions, and *dt* is nodes in the process tree.

$$S = 1 - \frac{\#da + \#ma}{\#nd + \#ec} \tag{9}$$

where *#da* is the number of duplicate activities, *#ma* is the number of missing activities, *#nd* is the number of nodes in the process tree, *#ec* is the number of event classes in the event log.

All of the above measurements were calculated for 11 ROC thresholds settings from 0 to 1, i.e. thresholds 0-0.1, 0.1-0.2, 0.2-0.3, 0.3-0.4, 0.4-0.5, 0.5-0.6, 0.6-0.7, 0.7-0.8, 0.8-0.9, and 0.9-0.1.

We performed the four dimensions quality calculations for the process models using Eqs. (6), (7), (8), and (9). Our calculations resulted in threshold 0.6 having the highest and most balanced scores of all the threshold settings. Table III describes our quality dimensions measurements.

Table III: Four quality dimensions measurements results.

T	***F***	***P***	***G***	***S***	**Trace references**
0	1.0	0.33	0.88	0.96	All references from σ1 to σ15
0.1	1.0	0.33	0.88	0.96	All references from σ1 to σ15
0.2	1.0	0.32	0.88	0.96	σ1, σ2, σ3, σ4, σ5, σ6, σ8, σ9, σ10, σ11, σ12, σ13, σ14, σ15
0.3	1.0	0.54	0.88	0.96	σ1, σ2, σ3, σ6, σ8, σ10, σ11, σ12, σ13, σ14, σ15
0.4	1.0	0.67	0.88	0.95	σ1, σ2, σ3, σ8, σ10, σ11, σ12, σ13, σ14, σ15
0.5	1.0	0.65	0.88	0.95	σ1, σ2, σ10, σ11, σ12, σ13, σ14, σ15
0.6	1.0	0.73	0.71	0.95	σ2, σ13, σ14, σ15
0.7	1.0	0.70	0.44	0.95	σ13, σ14, σ15
0.8	1.0	0.66	0.27	0.95	σ14, σ15
0.9	1.0	0.68	0.10	1.00	σ15
1	-	-	-	-	∅

2.5 Similarity measures

Once we had generated process models for each threshold, we computed similarity measures to compare the models with the synthetic SOP. In this study, we applied structural and behavioural similarity measures to improve the accuracy of similarity measures. We used Jaccard Coefficient Similarity in both structural and behavioural measures.

The standard formula of the Jaccard coefficient is as follows.

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|} \tag{10}$$

where J is similarity, A is a finite set of A, and B is a finite set of B.

A. Structural similarity

Structural similarity is a similarity metric between process models based on their structures. The most important aspect of calculating the structural similarity between two process models is the mapping of the components from the models that are being compared [11, 14]. Since we used BPMN models in this study, the components we mapped were edges, tasks, gateways, and transitions. The results of our structural similarity measures by adopting Eq. (10) are described in Table IV.

Table IV: Structural similarity measurements results.

	SOP							
	ed	***tk***	***g***	***t***	***e***			
	2	9	2	13	26			
	Structural similarity							
T_n	***ed***	***tk***	***g***	***t***	***e***	$\lvert SOP \cap P_{Tn} \rvert$	$\lvert SOP \cup P_{Tn} \rvert$	***SS***
0	2	9	12	28	51	26	51	0.51
0.1	2	9	12	28	51	26	51	0.51
0.2	2	9	12	28	51	26	51	0.51
0.3	2	9	10	25	46	26	46	0.57
0.4	2	9	8	22	41	26	41	0.63
0.5	2	9	8	22	41	26	41	0.63
0.6	2	9	4	16	31	26	31	0.84
0.7	2	9	4	16	31	26	31	0.84
0.8	2	9	4	16	31	26	31	0.84
0.9	2	9	2	13	26	26	26	1.00
1	0	0	0	0	0	0	0	0

Legend: *Tn* = process model of *n* threshold, *ed* = edges, *tk* = task, *g* = gateway, *t* = transitions, *e* = total number of elements, |*SOP*∩*PTn*| = intersection of SOP and process model of *n* threshold, |*SOP*∪*PTn*| = union of SOP and process model of *n* threshold, *SS* = structural similarity score.

However, in real-life scenarios, the results from the calculations tend to undermine the significance of the difference in real-life processes. Thus, we used the second similarity metric, behavioural similarity, as a way to balance the calculation results.

B. Behavioural similarity

The principle of behavioural similarity measure is to calculate the distances between the behaviours of two process models by following their causal footprints [6, 13]. In this paper, we adopted the Transition Adjacency Relation (TAR) concept that was first proposed in [29]. A TAR set can specify the footprint of processes as it maps transition sequences that appear in every probable firing sequence.

In the behavioural similarity measure, using the technique proposed by Zha et al. [29], we determined the TAR set of the synthetic SOP by using a matrix. The TAR set of synthetic SOP was {*AB*, *BC*, *CD*, *CE*, *DC*, *EF*, *FG*, *GH*, *HI*}, while the TAR sets of discovered process models can be seen in Table V.

Table V: Tar sets of process models of *n* threshold ($TART_n$).

T	***TART*$_n$**
0	{*AB, BC, CD, CE, CF, CG, CH, CI, DC, EF, EG, EH, EI, FG, FH, FI, GH, GI, HI*}
0.1	{*AB, BC, CD, CE, CF, CG, CH, CI, DC, EF, EG, EH, EI, FG, FH, FI, GH, GI, HI*}
0.2	{*AB, BC, CD, CE, CF, CG, CH, CI, DC, EF, EG, EH, EI, FG, FH, FI, GH, GI, HI*}
0.3	{*AB, BC, CD, CE, DC, EF, FG, FH, FI, GH, GI, HI*}
0.4	{*AB, BC, CD, CE, DC, EF, FG, GH, HI*}
0.5	{*AB, BC, CD, CE, DC, EF, FG, GH, HI*}
0.6	{*AB, BC, CD, CE, DC, EF, FG, GH, HI*}
0.7	{*AB, BC, CD, CE, DC, EF, FG, GH, HI*}
0.8	{*AB, BC, CD, CE, DC, EF, FG, GH, HI*}
0.9	{*AB, BC, CD, CE, DC, EF, FG, GH, HI*}
1	-

Once we had the TAR sets of the synthetic SOP and the process models discovered from each threshold setting, we calculated the similarity distances between reference SOP and all discovered models by using Eq. (10).

Table VI shows the behavioural similarity scores of the discovered models to the synthetic SOP.

Table VI: Behavioural similarity measurements results.

	SOP			
	e			
	9			
	Behavioural Similarity			
T_n	***e***	***| SOP ∩ P_{Tn} |***	***| SOP ∪ P_{Tn} |***	***BS***
0	19	9	19	0.47
0.1	19	9	19	0.47
0.2	19	9	19	0.47
0.3	12	9	12	0.75
0.4	9	9	9	1.00
0.5	9	9	9	1.00
0.6	9	9	9	1.00
0.7	9	9	9	1.00
0.8	9	9	9	1.00
0.9	9	9	9	1.00
1	0	0	0	0

BS = behavioural similarity score.

C. Normalized Similarity Score

We overcame the contradicting nature of the results from structural and behavioural measures by adopting a simple Arithmetic Mean formula (see Eq. (11)). As a result, we found the mean value is more representative of the similarity distance between the models in everyday application contexts.

$$S_n = \frac{1}{2}\sum_{i=1}^{2} x_i = \frac{SS\,(P_n,Sop) + BS\,(PT_n,Sop)}{2} \quad (11)$$

where *Sn* is the similarity score for a discovered process model of *n* threshold to the SOP, x_i is the value of each item in the list of numbers in search of the mean, *SS* (P_n,*Sop*) is the structural similarity score for a discovered process model of *n* threshold to the SOP, *BS* (PT_n,*Sop*) is behavioural similarity score for a discovered process model of *n* threshold to the SOP.

In the final step of our approach, once we have had both structural and behavioural similarity scores, we calculated the final similarity scores that represent both structural and behavioural perspectives using Eq. (11).

Table VII shows the results of our calculation, with threshold 0.9 having the highest similarity score.

Table VII: Normalised similarity measurements results.

T_n	*SS*	*BS*	S_n
0	0.51	0.47	0.49
0.1	0.51	0.47	0.49
0.2	0.51	0.47	0.49
0.3	0.57	0.75	0.66
0.4	0.63	1.00	0.82
0.5	0.63	1.00	0.82
0.6	0.84	1.00	0.92
0.7	0.84	1.00	0.92
0.8	0.84	1.00	0.92
0.9	1.00	1.00	1.00
1	0	0	0

S_n = final similarity score.

3. RESULTS AND DISCUSSION

This review of SOP model prediction used three methods: the ROC method, the Four Quality Dimension method, and the similarity measure method. We studied how adaptive these methods are in discovering models that were most similar to a hypothetical SOP. The three methods employed in this study yielded different results in making predictions about which threshold settings generate models that have the closest distance to the synthetic SOP.

The ROC method concluded that the threshold setting which predicted the best result was threshold 0.5 (see Table II and Fig. 3). On the other hand, the four quality dimensions calculations showed that the best prediction model could be generated from threshold 0.6 (see Table III). At the same time, similarity measures determined that threshold 0.9 generated the closest process model to the reference SOP (see Table VII).

In this study, we need first to acknowledge that the Similarity Measures served as the best predictor of process model alignment with the synthetic SOP as it directly compared the generated process models to the synthetic SOP rather than using other variables to make predictions of which threshold setting should produce the most similar process model to the synthetic SOP as in the other two methods. With that in consideration, the similarity measures in this paper were used as benchmarks to evaluate the performance of ROC and four quality dimensions methods.

Table VIII below shows the comparisons between the results from the three methods used in this study, with the best predictors for each method marked in bold.

Table VIII: Comparison of the measurements results.

T	*ROC*	*FQD*				*SM*
	ACC	*F*	*P*	*G*	*S*	S_n
0	0.75	1.0	0.33	0.88	0.96	0.49
0.1	0.75	1.0	0.33	0.88	0.96	0.49
0.2	0.77	1.0	0.32	0.88	0.96	0.49
0.3	0.86	1.0	0.54	0.88	0.96	0.66
0.4	0.88	1.0	0.67	0.88	0.95	0.82
0.5	**0.96**	1.0	0.65	0.88	0.95	0.82
0.6	0.34	**1.0**	**0.73**	**0.71**	**0.95**	0.92
0.7	0.26	1.0	0.70	0.44	0.95	0.92
0.8	0.25	1.0	0.66	0.27	0.95	0.92
0.9	0.26	1.0	0.68	0.10	1.00	**1.00**
1	0.25	0	0	0	0	0

FQD = four quality dimensions, *SM* = similarity measures.

4. CONCLUSION

This study has evaluated three different methods to find process models which were aligned to a synthetic SOP from pre-defined threshold settings. The methods used were ROC analysis, four quality dimensions, and similarity measures. The similarity measures in this study functioned as a benchmarking tool to evaluate the performance of the two other methods in making predictions of what thresholds were optimal to make the most similar process models to a synthetic SOP. The reason for this is that similarity measures used the synthetic SOP to compare the distance between models as opposed to the other two methods, which merely made predictions based on calculation variables without taking the synthetic SOP into account.

We found in this study that there were gaps between the aligned threshold discovered by similarity measures and the predictions generated from ROC and four quality dimensions. ROC analysis concluded that threshold 0.5 was the best predictor, and the four quality dimensions calculations resulted in threshold 0.6 as the best model. At the same time, similarity measures determined that threshold 0.9 was the most similar model to the synthetic SOP. In other words, what would be the best models predicted by ROC and four quality dimensions did not align with the synthetic SOP in this study. This unalignment is due to the nature of ROC and four quality dimensions methods encouraging variations in the process models while at the same time avoiding recommendations for over-fitting models as the best model by default. Our purpose in discovering process models that are aligned with a hypothetical SOP is to provide a reference on how processes should be executed in regard to the regulations applied in different organisations. Hence, over-fitting models can serve as the better options for this purpose.

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