Event Log-Based Fraud Rating Using Interval Type-2 Fuzzy Sets in Fuzzy AHP

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Abstract— **Fraud on the event logs derived from business process is known as event log-based fraud. Fraud detection using event logs employs process mining technique, notably conformance checking analysis. This study proposes a method for rating event log-based fraud datasets using fuzzy analytic hierarchy process (AHP), a well-known multicriteria decision-making method. Earlier studies proposed that interval type-2 fuzzy set provides an alternative in handling uncertainty than type-1 fuzzy set. Therefore, we utilize interval type-2 fuzzy sets in fuzzy AHP in order to manage vagueness in many linguistic judgement. This study includes linguistic hedges implementation to modify the membership function of expert valuation. The experimental results showed comparable types of membership function shape and its obtained accuracy performance. Obtained accuracy from fuzzy type-1 AHP method achieved 94% for triangular membership function shape and 93.9% for interval type-2 fuzzy AHP. Although there was no escalation in accuracy after applying interval-valued fuzzy sets for all scenarios, the rank of fraud weight in each feature were altered.**

Keywords—fraud rating, interval type-2 fuzzy sets, fuzzy AHP, even-log based fraud.

I. Introduction

Along with the increasing implementation of big data and mobile-computing technology, the number of fraudulent case also increases. A variety of approaches on computational intelligence based technique have been proposed to deal with fraud detection [1],[2]. Process mining – although relatively new discipline in data science knowledge – has already taken part in fraud detection [3],[4],[5]. Process mining works by extracting knowledge from event data that is available in the system [6]. Fraud detection in process mining is done by conformance analysis. Conformance analysis aims to check the conformity between predefined process model and real event log of the same process [7]. Outliers that are resulted from the comparison are considered as fraud.

Event log-based fraud is a fraud that arises in system's log files. It is caused by process deviations which occur in business processes. Historic data, i.e. event logs play significant role in fraud auditing. However, the auditors should be cautious when assessing an alleged fraudulent case. In order to avoid failing valuation of event logs based fraud, a multicriteria decision-making technique could be applied.

A useful method in multi criteria decision making is the AHP. The basic idea of AHP is to help decision maker in structuring the complexity of the problems by comparing in between some criteria and alternatives of choice [8]. The AHP technique can accommodate both qualitative and quantitative judgement. However, the AHP approach cannot handle the vagueness that exists in many decision making problems. Buckley [9] proposed a fuzzy sets implementation to substitute the crisp number of mapping one's perception criteria in AHP, called fuzzy AHP. This technique is considered to give a more precise judgement than the traditional AHP approaches.

The fuzzy AHP method makes use of the auditor's subjective concern when detecting fraud case. However, vagueness of the auditor's linguistics judgment is still a problem. With the emergence of type-2 fuzzy sets and interval type-2 fuzzy sets introduced by Zadeh [10], judgement could have more comprehensive evaluation owing to type-2 fuzzy set properties. The membership function in type-2 fuzzy set is useful for incorporating more uncertainty defined than type-1 fuzzy [11].Hence, the use of interval type-2 fuzzy sets in fuzzy AHP gives expansion in handling vagueness that is often encountered in assessing the auditor's linguistic judgment.

Chen and Lee [12] are the firsts who presented an operation of interval type-2 fuzzy sets in multicriteria decision-making method. They proposed a linguistic scale for the ratings of attribute in interval type-2 fuzzy sets were proposed. Following Chen's works, various expansion of interval type-2 fuzzy sets in multicriteria decision-making methods are elaborated [13],[14],[15]. Study [12] and [13] are describing the use of a new linguistic terms of interval type-2 fuzzy sets that deliberated a membership function shape being used in their approach. Kahraman [14] advanced steps of fuzzy AHP in his work and underlined his newly-proposed ranking method in terms of interval type-2 fuzzy sets. While Seda [15] is to employ interval type 2 fuzzy sets with TOPSIS method in case of supplier selection problems.

The approach proposed in this study is to utilize fuzzy AHP with interval type-2 fuzzy sets by combining the quantitative and qualitative judgement. Furthermore, triangular and trapezoidal membership function shapes are tested in searching for the optimum accuracy at classifying fraud case in testing data. An event log from a loan application in a bank is used for case study.

This paper begins with the advantages of interval type-2 fuzzy sets with fuzzy AHP. Then, a more detailed scope of work and some basic definition are given. In the next section, the results and discussion of this study are explained. Lastly, the conclusions are given in the last section.

II. METHODS

A. The Proposed Method

The proposed system involves two work stages : process mining and fraud classification. In the first stage, the process mining employs a modified of conformance checking plug-in for event-log based fraud applied in ProM 6.0 software. The result of this stage is a dataset that contains cases with number of features of fraud criteria detected from the given event logs. In the second stage, fraud classification is done by using interval type-2 fuzzy AHP for weighting the fraud case dataset given from the previous stages. These two stages is a novel hybrid method in terms of fraud detection. The general step of works in this study is shown in Figure 1.

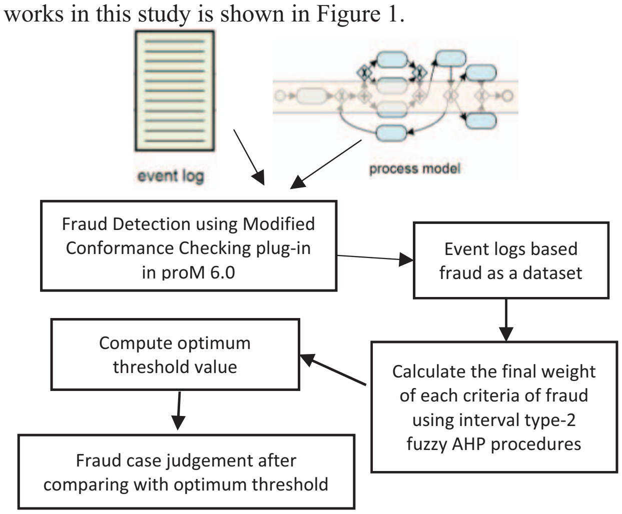

Fig. 1. Block diagram of proposed system design

B. Event-Log Based Fraud

The starting point of process mining is event log. An event log is a sequential log of event-related process in systems [6]. Event log has a list of properties, which generally includes case id, timestamps, activity and other additional process-related attributes such as resources, IP address, products, etc.

Previous study in fraud risk mitigation using process mining [4] described various criteria of fraud during process. Table 1 shows the criteria of fraud summarized from those study.

TABLE I. CRITERIA OF FRAUD AND ITS DESCRIPTION

Criteria of Fraud	Description
Skip Activity	Stepping out from a process sequence
Wrong Resources	Unauthorized originator executing an event
Wrong Duty	Same originator executing event that has different privilege
Wrong Pattern	A case where there is violation towards pattern from process models
Wrong Decision	The decision result does not comply with the SOP in process model
Wrong Throughput Time	Time execution is too long (ttmax) or too short (ttmin) compared to the standard execution time

C. Interval Type-2 Fuzzy Sets

A type-2 fuzzy set whose third-dimension value is the same everywhere is called interval type-2 fuzzy sets. No new information is stored in the third dimension of an interval type-2 fuzzy sets [16]. Therefore, interval type-2 fuzzy sets are much simpler in calculation than general type-2 fuzzy sets.

The linguistic judgement variables of type-1 and their type-2 for triangular and trapezoidal membership function are shown in Table. 2. In order to gain a larger set of values for linguistic variables from a few collection of primary terms, linguistic hedges are applied. Linguistic hedges change the shape of a fuzzy set (i.e the modified the membership function). The *modifiers* (hedges) are words like "more or less", "very" which changes the predicate. These modifiers transform original membership function $\mu(x) \rightarrow \mu^n(x)$, n > 1 (concentration) and n < 1 (dilution) [17] .

TABLE II. LINGUISTIC VARIABLES SCALE AND HEDGES OF TYPE-1 FUZZY SET & INTERVAL TYPE-2 FUZZY SET FOR TRIANGULAR (TFN) & TRAPEZOIDAL(TRFN) MEMBERSHIP FUNCTION

Lingustic Variables	TFN of type-1	TrFN of type-1	Interval TFN of type-2	Interval TrFN of type-2
Equally Important (EI)	(1,1,1)	(1,1,1,1)	(0.1,0.1,0.1;1) (0.1,0.1,0.1;0.9)	(0.1,0.1,0.1,0.1;1) (0.1,0.1,0.1,0.1;0.9)
Weak (W)	(0.5,1,1.5)	(0.5,1,1.5,2)	(0.05,0.1,0.15;1) (0.075,0.1,0.125;0.9)	(0.05,0.1,0.15,0.2;1) (0.075,0.1,0.15,0.175;0.9)
Fairly Important (F)	(1,1.5,2)	(1,1.5,2,2.5)	(0.1,0.15,0.2;1) (0.125,0.15,0.175;0.9)	(0.1,0.15,0.2,0.25;1) (0.125,0.15,0.175,0.225;0.9)
Important (IM)	(1.5,2,2.5)	(1.5,2,2.5,3)	(0.15,0.2,0.25;1) (0.175,0.2,0.225;0.9)	(0.15,0.2,0.25,0.3;1) (0.175,0.2,0.225,0.275;0.9)
Very Important (VI)	(2,2.5,3)	(2,2.5,3,3.5)	(0.2,0.25,0.3;1) (0.225,0.3,0.275;0.9)	(0.2,0.25,0.3,0.35;1) (0.225,0.3,0.275,0.325;0.9)
Very very important (VVI)	(4,6.25,9)	(4,6.25,9,12.25)	(0.04,0.0625,0.09;1)(0.05,0.09,0.07;0.9)	(0.04,0.0625,0.09,0.1225;1)(0.05,0.09,0.075,0.1;0.9)
Less Important (LIM)	(1.2,1.4,1.6)	(1.2,1.4,1.6,1.7)	(0.4,0.45,0.5;1)(0.41,0.45,0.47;0.9)	(0.4,0.45,0.5,0.55;1)((0.41,0.45,0.47,0.52;0.9)
Very Fairly Important (VF)	(1,2.25,4)	(1,2.25,4,6.25)	(0.01,0.0225,0.04;1)(0.016,0.0225,0.031;0.9)	(0.01,0.0225,0.04,0.0625;1)(0.016,0.0225,0.031,0.05;0.9)

D. Type-2 Fuzzy AHP

For the purpose of rating the fraud criteria, the type-2 fuzzy AHP is used to obtain the weight vector of each criterion. The type-2 fuzzy AHP operation is essentially the same with the traditional AHP. The procedure of type-2 fuzzy AHP applied in this study is basically advanced from Buckley [9] F-AHP for fuzzy type-1. Hence, the procedure of the proposed method of interval type-2 fuzzy AHP in this study are described as follow:

- Step 1 : Construct the pairwise matrices of all criteria given by the expert judgement using linguistic scale variables.
- Step 2 : Calculate the geometric mean of each row in pairwise matrices .
- Step 3 : Construct the fuzzy weight decision matrix which was derived from normalization. The normalization of fuzzy weight for each row is computed.

  The interval type-2 fuzzy weight for each criterion are defuziffied using Kahraman [14], proposed method of $DTraT$ for trapezoidal fuzzy number and $DTriT$ for triangular trapezoidal fuzzy number. The following are the calculation of $DTriT$ and $DTraT$ method :

$$DTriT = \frac{\frac{(u_U - l_U) + (m_U - l_U)}{3} + l_U + \alpha\left[\frac{(u_L - l_L) + (m_L - l_L)}{3} + l_L\right]}{2} \quad \text{(Eq.1)}$$

$$DTraT = \frac{\frac{(u_U - l_U) + (\beta_U \cdot m_{1U} - l_U) + (\alpha_U \cdot m_{2U} - l_U)}{4} + l_U + \left[\frac{(u_L - l_L) + (\beta_L \cdot m_{1L} - l_L) + (\alpha_L \cdot m_{2L} - l_L)}{4} + l_L\right]}{2} \quad \text{(Eq.2)}$$

- Step 4. The final fraud weight of each case is obtained by multiplying the number of cases detected for each feature of fraud with the weight of each feature from the fuzzy weight decision matrix resulted in step 3.
- Step 5. Compute the optimum threshold from final weight of each case in dataset training. The optimum threshold is used for classifying whether a case is deemed as 'fraud' or 'normal' case. The optimum threshold is determined by generating threshold from 0.001 to maximum final weight recorded in the dataset. The optimum threshold should have maximum accuracy number. The accuracy number is calculated using Receiver Operating Characteristic (ROC) based on the values of true positive, false positive, true negative and false negative variables.

III. Results And Discussion

In this section, we explore the implementation of the proposed method for rating fraud cases based on interval type-2 fuzzy AHP. From the 17,515 events available in event logs data of consumer loan application in a bank, the conformance checking plug-in detected 130 cases of event logs based fraud, which comprised of 100 cases labeled as fraud and 30 cases labeled as normal. The dataset was used as training dataset for the classification in the next step. For the testing dataset, we used 100 case event log-based fraud with 70 cases labeled as fraud and 30 cases as normal.

The second stage of the proposed method is following the steps given in the previous section.

Step 1. Build the hierarchy of fraud criteria (Figure 2.)

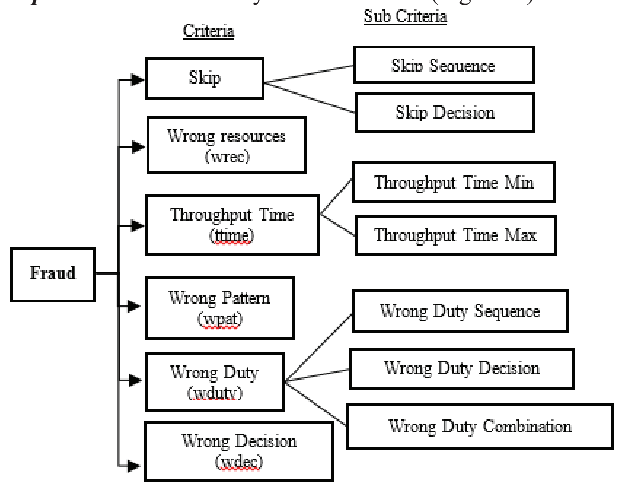

Fig. 2. The hierarchy of event log-based fraud criteria

Then, a pairwise comparison of matrices from expert valuation towards each criteria and sub criteria of fraud in event logs using linguistic variables were constructed as following:

$$\text{Criteria} = \begin{bmatrix} ei & w & im & f & im & f \\ 1/w & ei & f & w & f & 1/f \\ 1/im & 1/f & ei & 1/f & f & 1/f \\ 1/f & 1/w & f & ei & f & 1/im \\ 1/im & 1/f & 1/f & 1/f & ei & 1/vi \\ 1/f & f & f & im & vi & ei \end{bmatrix}$$

$$\begin{array}{c}\text{Criteria} = \\ \text{(with linguistic} \\ \text{hedges)}\end{array} \begin{bmatrix} ei & w & lim & f & im & vf \\ 1/w & ei & f & w & lf & 1/f \\ 1/lim & 1/f & ei & 1/vf & f & 1/lf \\ 1/f & 1/w & vf & ei & f & 1/vi \\ 1/im & 1/lf & 1/f & 1/f & ei & 1/vvi \\ 1/vf & f & lf & vi & vvi & ei \end{bmatrix}$$

$$\text{Skip} = \begin{bmatrix} ei & 1/f \\ f & ei \end{bmatrix} \qquad \text{Throughput Time} = \begin{bmatrix} ei & w \\ 1/w & ei \end{bmatrix}$$

$$\text{Wrong Duty} = \begin{bmatrix} ei & im & 1/f \\ 1/im & ei & f \\ f & 1/f & ei \end{bmatrix}$$

Step 2. Using the data represented in pairwise comparison matrices of fuzzy sets criteria derive from matrices criteria. Calculate the the geometric mean for each row.

Step 3. Construct the fuzzy weight decision matrices for each criterion. To defuzzify the final weight use Eq. 1 or Eq. 2 depending on the membership function being used. Then, calculate the normalized crisp weights.

Using the same procedure above, the fraud criteria weight of the other scenarios of selection membership function are calculated as shown in Table 3.

TABLE III. EXPERIMENT RESULTS OF EXPERT VALUATION IN LINGUISTIC VARIABLES AND LINGUISTIC VARIABLES WITH HEDGES

Method applied and MF Shape	Linguistic Variable			Linguistic Variable with Hedges		
	Obtained Accuracy	Opt. Threshold	Fraud Criteria Rank according to the weight	Obtained Accuracy	Opt. Threshold	Fraud Criteria Rank according to the weight
AHP	92%	0.033	Skip > wdec > ttime > wduty > wrec > wpat	92 %	0.033	Skip > wdec > ttime > wduty > wrec > wpat
FUZZY AHP						
TFN	94 %	0.031	Wdec >skip > wduty > ttime > wrec > wpat	94 %	0.031	Wdec >skip > wduty > ttime > wrec > wpat
TRFN	93 %	0.03	Wdec > wrec > ttime > wpat > skip > wduty	93 %	0.03	Wdec > wrec > ttime > wpat > skip > wduty
INTERVAL TYPE-2 FUZZY AHP						
TFN	93.9 %	0.035	Wrec > wdec > wpat > ttime > wduty > skip	93.9 %	0.035	Wrec > wdec > wpat > ttime > wduty > skip
TrFN	93.9 %	0.031	Wdec > wrec > wpat > skip > ttime > wduty	93.9 %	0.031	Wdec > wrec > wpat > skip > ttime > wduty
Asymmetrical TFN	93.9 %	0.032	Wdec > wrec > wpat > ttime > skip > wduty	93.9 %	0.032	Wdec > wrec > wpat > ttime > skip > wduty
Asymmetrical TrFN	93.9%	0.028	Wdec > wrec > ttime > wpat > skip > wduty	93.9%	0.028	Wdec > wrec > ttime > wpat > skip > wduty

Based on the experiment results shown in Table 3, the accuracy obtained under fuzzy AHP method is gained in number. We can see that the triangular membership function offers better accuracy than trapezoidal shape for both circumstances. It occurs since the context of fraud case only has an element which fully belongs to the set.

For interval type-2 fuzzy sets, the result shows no increase in accuracy from the fuzzy type-1 AHP. Even though, Kahraman [14] thoughts in his study that the use of interval type-2 fuzzy sets would exhibit significant distinction in the results compare to type-1 fuzzy AHP. Nevertheless, the rank of fraud criteria according to the weight for each scenario is changed. The shifting of fraud rank criteria was driven by uncertainty modeled in linguistic variables of interval type-2 fuzzy sets.

IV. CONCLUSION

This paper proposes interval type-2 fuzzy sets in analytical hierarchy process for weighting the fraud case detected using process mining. The interval type-2 fuzzy AHP for rating fraud problems has been developed for the first time in this study. The proposed method of AHP in this study combine qualitative and quantitative marking. That make a distinction with the method proposed by Kahraman [14]. The TFN type-1 fuzzy sets has resulted in better accuracy than the TrFN type-1, whereas in interval type-2 fuzzy sets the obtained accuracy is the same with fuzzy AHP. In the case of rating fraud case, the difference between interval type-2 fuzzy sets with type-1 fuzzy sets AHP lies in the shift of fraud rank criteria based on linguistic variables implementation. Linguistic hedges have been also developed to be used as another scenario of implementation. Further exploration in optimization technique to determine the membership function of interval type-2 fuzzy are needed to be performed in the future.

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