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Performance Evaluation and Selection of Financial Fraud Detection Models using MCDM Approach

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Abstract— **Evaluation of Fraud detection models is incredibly difficult due to the lack of objective performance measures. Since the evaluation of these models normally depends upon multiple attributes, it can be shaped as a multi-criteria decision making (MCDM) problem. The present research emphasizes on the development of MCDM approach to get a comprehensive ranking for the selection purpose by evaluating the various models based on the multiple attributes in the province of financial risks. An experimental study followed by methodology validation is also designed to validate the adopted MCDM approach using existing MCDM methods, 16-fraud detection models and 10-selection criteria. A comprehensive ranking of the models is obtained as the result of this study that shows the cogency and credibility of MCDM approach in the evaluation and selection of fraud detection models concerning especially with the financial risk.**

Index Terms— **Fraud Detection, Multi-Criteria Decision Making, Selection criteria, Ranking.**

I. INTRODUCTION

The rapid advancements in the information and communication technologies have forced our society towards the digitization of the various processes followed in each sector as banking, insurance, telecommunication and networking etc. One of the most remarkable examples of the digitization that can be observed in the society over the few years is the accretion of the credit card usage. Credit card has become an effective and factual standard for making online payment in the new business strategy named as electronic-commerce (E-commerce). This drastic evolution further leads to a very challenging and forthcoming problem of the fraud occurrence while making any online payment that can make a hazardous effect on the individual's wealth. Fraud may be referred as financial unlawful loss/advantage by the mean of implicit/explicit deceit. In other words, Fraud embraces unfair means devised by any human to gain some advantage over another human [1]. The statistical data concerning the fraud represented in cyber source report depict that the loss due to the frauds ranges from 0.9% - 3.2% in last ten years. The popularity of this fraud occurrence problem can also be observed from the data published by ISI web of Knowledge data that shows the huge availability of the articles concerning to the fraud occurrence and detection. The undesired and harmful consequences of the fraud occurrence direct the researcher's keen interest towards the development of fraud detection models. An integrated credit card fraud detection model based on Dempster Shafer Theory, Rule-based system and Bayesian learning by combining the transaction evidences current and past spending behavior of customer [2]. In the contemporary work, the concept of Bayesian learning was integrated by the researchers with neural networks and max entropy approaches to develop fraud detection models [3], [4], [5]. Further, the data mining approaches as decision trees, regression, support vector machine, association rules and neural network came into the existence for the development of fraud detection models [6], [7], [8], [9], [10]. In 2014, the researchers proposed a framework for fraud detection based on hidden Markov model that was capable to receive each and every incoming transaction and to check its behavior concerning to the frauds [11]. Later, some researchers argue that the computational intelligence techniques, namely particle swarm optimization, genetic algorithm, self organizing map and game theory, etc. may have the significant impact on the fraud detection process involved in online payments through any channel as debit/credit cards [12], [13], [14], [15], [16]. The extensive study about the existing fraud detection models reveals that the classification of these models can be made on the basis of implementing techniques into three major categories namely descriptive models, predictive models and artificial and computational models. The high availability of the fraud detection models provided by the various researchers in the past raised a new problem of the optimal selection of these models because the decision to pick a particular model for any financial institutions seems to be very tough. Some researchers represent the fraud detection model selection problem as multi-criteria decision making that shows the involvement of the multiple attribute in the evaluation process. Generally, the attributes, namely True positive rate (TP rate), False positive rate (FP rate) and accuracy have been widely considered in the past researches concerning to this selection problem [5], [17], [18]. The rest of the paper is organized as: section-2 provides the problem formulation, section-3 describes the research methodology and section-4 shows the experimental setup with methodology validation followed by results in section-5 and conclusions in section-6.

II. PROBLEM FORMULATION

Assessing the quality of fraud detection models is one of the elementary questions that must be addressed in this evaluation and selection process. Although it seems extremely hard due to the shortage of selection criteria for the evaluation purpose, it is of great importance for the financial analysis in any country. Since this selection process may involve a number of conflicting selection attributes, the present problem can be shaped as a MCDM problem. MCDM approach involves the evaluation of various alternatives on an identified set of selection criteria/attributes for their selection purpose. The present research focuses on the development of an MCDM approach for the optimal selection of fraud detection models. The empirical study considered here involve 16 credit card fraud detection models, 10- selection criteria and 1-MCDM approach to show the utility and the applicability of the develop evaluation and selection approach. The hierarchical structure of the present selection problem is provided in Figure 1 that shows the three level hierarchy, goal in the first level, selection criteria in the second level and the alternatives at the third level.

III. Research Methodology

The MCDM method proposed in this research for the optimal selection of credit card fraud detection models, namely,

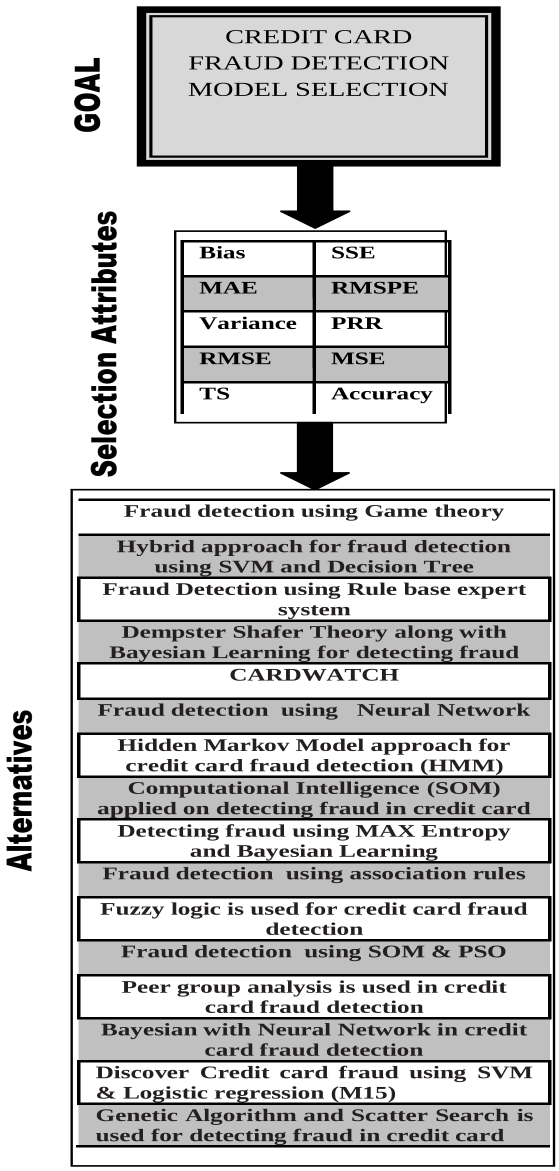


Fig. 1. Hierarchical Structure of the Fraud Detection model

Visekriterijumsko Kompromisno Rangiranje (VIKOR) was developed by Opricovic in 1998 for multi-criteria optimization of the highly complex systems that introduces multi-criteria ranking index based on the aggregate function showing "relative closeness of each alternative to the ideal alternative" originated in compromise ranking methods [19]. In this method, evaluation of each alternative to each selection criterion function takes place by implementing the linear

normalization concept for the elimination of units of the selection criterion functions [20]. The multi-criteria compromise ranking measure is developed in this method by using L_P-metric that is used in the compromising programming method [21, 22]. Let us suppose we have 'n' alternatives as $a_1, a_2, \ldots\ldots\ldots, a_n$, then rating of j^{th} aspect can be denoted by f_{in} i.e. it is the value of j^{th} selection criteria function for alternative a_n ; 'm' is the total number of selection criteria. This L_P-metric used here can be represented as given below in (1).

$$L_{P,n} = \left\{ \sum_{j=1}^{m} \left[w_j \left(f_j^* - f_n^j \right) / \left(f_j^* - f_j^- \right) \right]^p \right\}^{1/p} \quad (1)$$

$$where\ 1 \le p \le \infty; n = 1, 2, \ldots., n.$$

In VIKOR, $L_{1,n}$ and $L_{\infty,n}$ are used for the formulation of ranking measure denoted by A_n and B_n as shown in (2) and (3) and the solutions obtained from these two depict maximum group utility and minimum individual alternative lament of the "challenger". The compromise feasible solution as denoted by f^c is considered closest to the ideal alternative f^*. Here the word compromise emphasizes on the mutual consent agreement by

$\Delta f_1 = f_1^* - f_1^c$ and $\Delta f_2 = f_2^* - f_2^c$ as given in Figure 2.

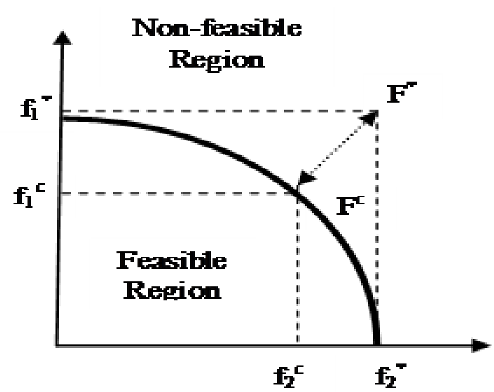


Fig. 2. Ideal and Compromise Solutions in VIKOR

The following steps are followed in VIKOR method as:

(i) Calculate the f_j^* and f_j^- values. If the j^{th} function shows the benefit then

$$f_j^* = \max_n f_{jn} \qquad f_j^- = \min_n f_{jn}$$

(ii) Determine the A_n and B_n

Fig. 2. Ideal and Compromise Solutions in VIKOR

$$A_n = \sum_{j=1}^{m} w_j \left(f_j^* - f_{in} \right) / \left(f_j^* - f_j^- \right) \quad (2)$$

$$R_n = \max_j \left[w_j \left(f_j^* - f_{jn} \right) / \left(f_j^* - f_j^- \right) \right] \quad (3)$$

Where w_i represent the relative importance of the selection criteria.

(iii) Calculate the $C_n, n = 1, 2, \ldots\ldots, N$ at v=0.05 as

$$C_n = v(A_n - A^*)/(A^- - A^*) + (1-v)(B_n - B^*)/(B^- - B^*)$$

Where

$$A^* = \min_n A_n,\ A^- = \max_n A_n$$

$$B^* = \min_n B_n,\ B^- = \max_n B_n$$

(iv) Sort the values of A, B and C in decreasing order to get the rankings of various alternatives.

(v) Make a compromise solution for the best ranked alternative say (a_1) by the measure C (minimum) if some conditions satisfy as under:

1. Acceptable advantage: $C(a_2) - C(a_1) \geq DC$ where a_2 is the alternative having second rank and $DC = 1/(m-1)$.

2. Acceptable stability under decision making: Alternative a' must also be ranked at top position or best rank on the basis of the values A and/or B on v=0.05.

If any of the above two conditions fails, in that case a comprise solution is proposed as

1. a_1 and a_2 if only second condition is not satisfied, or

2. $a_1, a_2, \ldots, a_n$, if first condition is not satisfied and a^n is determined by $C(a^n) - C(a_1) < DC$.

Finally, a comprise ranking of the alternatives has been obtained as the result of VIKOR method. The alternative having the minimum value of C will occupy the top position, i.e. rank-1 and the alternative having maximum value of C will be placed at the last position i.e. last rank.

IV. Empirical Study

To show the applicability of the proposed research methodology, i.e. VIKOR MCDM approach for the selection of fraud detection models, four banking datasets having different sizes depending on the number of transactions (500, 1000, 1500, 2000) were considered in this study. Further, 16-credit card fraud detection models namely [2-17]; Fraud detection using Game theory (M1), Hybrid approach for fraud detection using SVM and Decision Tree and (M2), Fraud detection using SOM & PSO (M3), Dempster Shafer Theory along with Bayesian Learning for detecting fraud (M4), CARDWATCH (M5), Fraud Detection using neural network (M6), Hidden Markov Model approach for credit card fraud detection (M7), Computational Intelligence (SOM) applied on detecting fraud in credit card (M8), Genetic Algorithm and Scatter Search is used for detecting fraud in credit card (M9), Fraud detection using association rules (M10), Fuzzy logic is used for credit card fraud detection (M11), Fraud Detection using Rule base expert system (M12), Peer group analysis is used in credit card fraud detection (M13), Bayesian with Neural Network in credit card fraud detection (M14), Discover Credit card fraud using SVM & Logistic regression (M15), Detecting fraud using MAX Entropy and Bayesian Learning (M16) are evaluated on the basis of 10-selection criteria as Bias (C1), Sum of Squared Error (C2), Mean Squared error (C3), Root Mean Square error (C4), Mean Absolute error (C5), Root Mean Square Prediction Error (C6), Theil Statistic (C7), Variance (C8), Predictive-ratio risk (C9), Accuracy (C10). The relative importance of all the selection criteria is considered is unity. The description of all selection criteria is provided in Table 1 [23], [24], [25], [26],

TABLE I
DESCRIPTION OF SELECTION CRITERIA USED IN THIS STUDY

Selection Criteria	Description
C1	$\frac{\sum_{i=1}^{n}(E_i - O_i)}{n}$
C2	$\sum_{i=1}^{n}(E_i - O_i)^2$
C3	$\frac{\sum_{i=1}^{n}(E_i - O_i)^2}{n}$
C4	$\sqrt{\frac{\sum_{i=1}^{n}(E_i - O_i)^2}{n}}$
C5	$\frac{\sum_{i=1}^{n}\lvert(E_i - O_i)\rvert}{n}$
C6	$\sqrt{Variance^2 + Bias^2}$
C7	$\sqrt{\frac{\sum_{i=1}^{n}\left((E_i - O_i)\right)^2}{\sum_{i=1}^{n}(O_i)^2}}$
C8	$\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left((E_i - O_i) - Bias\right)^2}$
C9	$\sum_{i=1}^{n}\frac{(E_i - O_i)}{E_i}$
C10	(TP+TN) / (TP+FP+FN+TN)

E_i, O_i: Estimated (predicted) and Observed (Actual) number of fraudulent transactions respectively in i^{th} number of dataset, TP: True Positive, TN: True Negative, FN: False Negative, FP: False Positive

f_2^c f_2^*

[27].

Now, at the first step of evaluation process, all the models are evaluated against the selection criteria using the standard equations as provided in Table 1 and the performance ratings of each model so obtained are provided in Table 2.

TABLE II
CALCULATED PERFORMANCE RATINGS OF MODELS

Models/Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
M1	17.25	1247	311.75	17.656	17.25	17.424	0.585	2.454	2.458	77.23
M2	12.75	689	172.25	13.124	12.75	12.790	0.376	1.010	1.629	82.14
M3	16	1082	270.5	16.447	16	16.258	0.525	2.887	2.141	84.45
M4	12.25	713	178.25	13.351	12.25	12.251	0.374	0.144	1.643	92.3
M5	14.25	1031	257.75	16.055	14.25	14.257	0.473	0.433	2.206	85.32
M6	5.25	193	48.25	6.946	5.25	5.923	0.160	2.742	0.742	83.57
M7	10.75	489	122.25	11.057	10.75	10.759	0.292	0.433	1.451	90.13
M8	14.75	981	245.25	15.660	14.75	14.835	0.462	1.588	2.327	87.36
M9	11.75	569	142.25	11.927	11.75	11.751	0.329	0.144	1.542	92.32
M10	8	278	69.5	8.337	8	8.021	0.206	0.577	0.972	78.26
M11	11.5	646	161.5	12.708	11.5	12.503	0.358	4.907	1.275	88.79
M12	14.25	831	207.75	14.414	14.25	14.373	0.424	1.876	1.973	93.12
M13	9.5	430	107.5	10.368	9.5	9.609	0.273	1.443	1.068	79.34
M14	14.25	813	203.25	14.257	14.25	14.251	0.419	0.144	2.076	88.96
M15	9.25	399	99.75	9.987	9.25	9.305	0.250	1.010	1.327	89.34
M16	13	744	186	13.638	13	13.115	0.396	1.732	1.615	90.34

Once the performance ratings have been obtained, the proposed MCDM approach, namely VIKOR has been implemented to get the final ranking based on the calculated score value (C) of each

TABLE III
RANKINGS OF 16-FRAUD DETECTION MODELS OBTAINED FROM VIKOR

Fraud Detection Models	Score value	Rank
M1	0.500	6
M2	0.539	7
M3	0.034	1
M4	0.713	11
M5	0.543	8
M6	1.000	16
M7	0.739	12
M8	0.249	3
M9	0.759	14
M10	0.903	15
M11	0.355	5
M12	0.209	2
M13	0.740	13
M14	0.651	9
M15	0.655	10
M16	0.311	4

model. The rankings of 16-fraud detection models so obtained are provided in Table 3.

In order to validate the proposed methodology, the same selection problem is also solved using two well known MCDM approaches, namely Analytical Hierarchy Processing (AHP) developed by Saaty in 1970 and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) developed by Hwang and Yoon in 1981 [28, 29]. Once comparison statistics of the rankings of 16-fraud detection models obtained from three methodologies as VIKOR, AHP and TOPSIS is obtained, Spearman's Rank correlation test is also performed to check the relationship existence between the rankings obtained from these three. In this test, the value of Spearman rank is to be calculated and any value between -1 and 1 is considered good. The Spearman rank's value represents the strong positive

TABLE IV
COMPARATIVE RANKINGS OBTAINED FROM VIKOR, AHP AND TOPSIS

Model	VIKOR (V)	AHP (A)	TOPSIS (T)	D=V-A	D=V-T
M1	6	1	2	5	4
M2	7	9	9	-2	-2
M3	1	2	1	-1	0
M4	11	8	10	3	1
M5	8	3	6	5	2
M6	16	16	12	0	4
M7	12	12	14	0	-2
M8	3	4	4	-1	-1
M9	14	11	11	3	3
M10	15	15	16	0	-1
M11	5	10	3	-5	2
M12	2	5	5	-3	-3
M13	13	13	13	0	0
M14	9	6	8	3	1
M15	10	14	15	-4	-5
M16	4	7	7	-3	-3

TABLE V
SPEARMAN'S RANK CORRELATION TEST STATISTICS

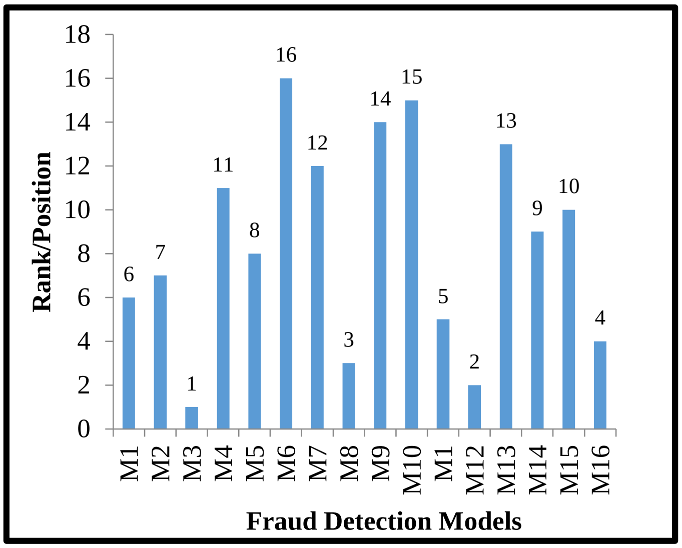
Set of Ranking Methods	(V-A)	(V-T)
Squared Sum $(\sum d^2)$	142	104
Spearman's Rank Correlation Coefficient (r_s)	0.791	0.847

relationship as closest to 1 and vice-versa. The Spearman's rank correlation test statistics are further provided in Tables 4 and 5.

V. RESULTS

Fig. 4. Comparative Rankings obtained from VIKOR, AHP and TOPSIS

According to the VIKOR MCDM method, the alternative having minimum score value will be placed at the top position and the alternative having maximum score value will be placed at the last position. The ranking results provided in Table 3 depicts that Fraud detection using SOM & PSO (M3) model is ranked at the top place, i.e. rank-1 having minimum score value

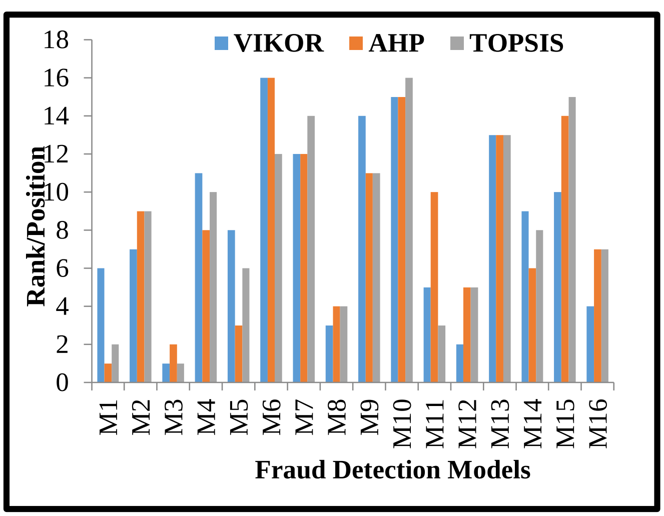


as 0.034 as compared to other models followed by Fraud Detection using Rule base expert system (M12) at rank-2 having score value as 0.209. The model, namely Fraud Detection using neural network (M6) has been placed at last

Fig. 3. Rankings of Fraud Detection Models obtained from VIKOR

position or rank-16 due to its maximum score value as 1.000. The rankings of all 16-fraud detection models obtained from VIKOR are also represented in Figure 3 given below.

Further, a novel attempt is made to validate the proposed VIKOR MCDM methodology by carrying out a correlation test.



The Spearman's rank correlation statistics provided in Table 5 shows the calculated value of Spearman's rank as 0.791 and 0.847 in both the cases as VIKOR-AHP and VIKOR-TOPSIS respectively. The calculated rank values depict that there exists a strong positive relationship between the rankings obtained from VIKOR, AHP and TOPSIS. The comparative rankings obtained from these three methodologies are further represented in Figure 4.

VI. Conclusion

Fraud detection is one of the most crucial aspects concerning to the financial scenario of today's modern society. The necessity of developing an efficient credit card fraud detection system has drawn keen interest of the researchers in this area and a variety of fraud detection models have been proposed for the same purpose in the past. Every fraud detection model is capable to detect the fraud to some extent up-to their inherent capabilities. The present study addresses the problem of optimal selection of credit card fraud detection models by shaping it as a MCDM problem. A number of MCDM approaches have been successfully implemented by the various researchers to solve so many real life problems in different areas [30], [31], [32], [33], [34], [35], [36], [37], [38], [39]. The deep study of the past researches reveals that TP Rate, FP Rate and accuracy are the most commonly used selection parameters used for the evaluation of fraud detection models. In the present study, we have introduced nine more selection criteria as provided in Table 1 that can contribute a lot in this evaluation process. The VIKOR MCDM method has been implemented for the first time to solve the present selection problem that provides the comprise ranking of the various alternatives by accommodating the selection criteria weights and it is very simple to implement because it depends on straightforward mathematics algebraic equations. The present work can be enhanced by adopting multiple MCDM approaches, considering variable weights of the selection criteria and carrying out the sensitivity analysis to check the criticality of the selection criteria in the evaluation of various fraud detection models.

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