Intl. J. Humanities (2015) Vol. 22 (4): (97-114)

A New Decision Making Tool for Feature Selection and Credit Evaluation of Loan Applicants

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Received: 2015/5/15 Accepted: 2016/3/18

Abstract

In this study, an evaluation model is developed to assess the credibility of the loan applicants. The proposed model is a multicriteria decision making (MCDM) problem consisting of numerous criteria by integrating analytic hierarchy process (AHP) and genetic algorithm (GA). In the case of apparent consensus for several measures, the research clearly indicates that both quantitative and qualitative information must be employed in evaluating loan applicants. The AHP approach is widely used for MCDM in various scopes. In 2008 Lin et al proposed the adaptive AHP approach (A^3)in order to decrease the number of steps for checking the inconsistency in the AHP model. The study presents a MCDM model by developing the new adaptive AHP approach (N_A^3) already proposed by Herrera-Viedma in 2004. The proposed model has led to fewer calculations, and less complexity. The model was applied to 200 clients in order to show its efficiency and applicability. A brief look at the implementation of the model showed that it is significantly valid in selecting clients with respect to the known criteria, besides decision making regarding the determination of the assessment factors.

Keywords: New adaptive AHP approach (N_A^3); Feature selection; Credit evaluation; Banking

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1. Introduction

During recent decades, the banks have been increasingly investing in the assessment models and development of expert systems for evaluating loan applicants. Calculation technique is one of the ways for banks to reduce risks and probability of loans failure, but qualitative criteria and external factors such as economic and scientific requirements force them to review the decision-making methods. Therefore, expert systems and tools with automatic decision-making lead to improve the client assessment processes.

The credit client assessment is difficult for managers because of multiple interrelated criteria and quantitative and qualitative factors (Huang et al., 2008). Lorie and Savage (1955) proposed a classic method for selecting clients that could be accepted or rejected on a number of available applications. In the literature, there are several methods for the assessment and credit client rating. These methods include AHP (Chin et al., 2008), fuzzy AHP (Tang et al., 2005), scoring models (Wey, 2005), ranking model (Seyedhoseini et al., 2009), mathematical models (Mahmudi et al., 2009), rough set models (Wang et al., 2012), Genetic Programming (GP) (Abdou, 2009; Chi et al., 2012), Artificial Neural Network (Abdou, 2008), and Benchmarking Models (Shen et al., 2012).

Even with a large number of proposed models, the assessment of credit client remains problematic so that few models have gained wide acceptance. Though computer-based models have certain desired features, the use is also not well accepted due to complex time consuming calculations (Huang et al., 2008; Cui et al., 2008). Hence, none of these models have dealt with feature selection and assessment simultaneously by considering both quantitative and qualitative criteria in the structure of an expert system.

Expert systems utilize a set of rules to solve the problems. Thus, rule-based expert systems attempt to imitate expert's behavior (Wey, 2005). Because of the limited resources of bank, national industrial development requires a proper selection of the credit clients. Using valid approaches based on scientific foundations determine criteria for budget allocation and prevents the selection of non-profitable or unfeasible applicants (Unido, 1985). In developing countries, regarding the general features and characteristics of these countries, issues, and obstacles that every country faces in practically evaluating its economic, technical, managerial, and social conditions, this context has not gained much attention. However, regarding the limited financial resources, the best budget allocation in these countries is of great importance. The Empirical assessment of credit client in developing countries due to invalidity and lack of information and statistics are often incomplete or inefficient. Generally, there has been no long-standing analysis in accordance with technical assessment principles.

The number of previous studies which consider multiple interrelated criteria such as technical knowledge, economic, financial and technical feasibility conformity, mission-oriented, and available resource's for assessment, and budget allocation of client selection is relatively low (Chen, 2012; Dinh et al., 2007; Gönen et al., 2000; Marshall et al., 2010; Aliheidari Bioki et al., 2013). In addition, there is no expert model to consider both quantitative and qualitative criteria while using the fewest rules and regulations to assess. Therefore, in this paper, both quantitative and qualitative assessments of loan applicant is done simultaneously, i.e. financial, economic, technical, applied factor, risk appetite, feasibility, technical, and managerial competencies are evaluated simultaneously .Furthermore, an expert model which is developed and improved by new adaptive AHP approach (N_A^3), has been developed for the assessment and decision-making in budget and loan allocation.

The remainder of this paper is organized as follows: Section 1.1 is devoted to introduce the well-known A^3 method presented by Lin et al., (2008) and Section 1.1 briefly presents the AHP approach introduced by Herrera-Viedma (2004). The details of the research methodology are illustrated in section 2. Then in section 3, designing the assessment model by proposing N_A^3 is presented. Section 4 discusses the model development and experimental details, and Section 5 presents the final decision making engine. The validity of the model is verified in section 6 using the real results. The last section is devoted to the Summary, Conclusion, Limitations and Suggestions for future research.

1.1. Adaptive AHP Approach (A^3)

In 2008, Lin et al. proposed the adaptive AHP approach (A^3) method which used a soft computing scheme, Genetic Algorithm (GA), to recover the real number weightings of the various criteria in AHP and provided a function for automatically improving the consistency ratio of pair wise comparisons (Lin et al., (2008).

Saaty proposed a method of measuring Consistency Ratio (CR) (see Saaty, 1980). If CR exceeds 0.10, the pair wise comparison needs to be reassessed. The reassessment process is boring and does not guarantee the consistency of pairwise comparisons. Thus, another reassessment is necessary if the resulting CR remains unsatisfactory. Reassessment is simply too expensive for sorting out inconsistencies (Tam et al., 2006). In the investigation of Lin et al., (2008), the A^3 method using GA is developed to recover the continuous relative importance weights of the various criteria based on two objective values: (1) CR, and (2) the difference of the derived PWM from the initial PWM. In this method, the search process of GA is guided by minimizing CR; it results in an adapted PWM with lower CR, which is acceptable in terms of the consistency requirements of AHP. The search process is also guided by minimizing the difference from the initial PWM. Thus, the resulting PWM reserves the original beliefs of the decision maker (DM) regarding the relative importance relationship among the criteria. Although the A^3 provides an automatic mechanism for improving CR, it depends on initial assessment (original PWM). It causes the result of model that is related to subjective decision. For overcoming this shortcoming, the A^3 model has been improved and integrated with Herrera-Viedma' model and a new adaptive AHP approach (N_A^3).Speed of implementation, low cost, ability of both subjective and objective decision, ability of analyzing several scenarios in short time are some of the N_A^{3}advantages. Additionally with proposed model, we can recover the real number weightings based on subjective and objective decision of the various criteria in A^3 model and provide a function to improve automatically consistency ratio of pair wise comparisons and cover nonlinear relationships of PWM.

1.2. AHP and consistent fuzzy preference relations

The AHP is based on pair wise comparison judgments and can provide a flexible and powerful tool to address both qualitative and quantitative multi-criteria problems, which is developed by Saaty (1980). Its main distinction is that AHP has been applied to a wide variety of decisions (Ngai et al, 2005). AHP provides an estimate of additive utility weight that best matches the initial information provided by the decision-maker and it provides a meaningful way to measure and combine tangible and intangible criteria in any decision (Kokangul et al, 2009). The traditional AHP uses n×(n-1)/2 judgments in a preference matrix with *n* alternatives. Because of that, it takes a long time to collect judgments and to do the calculations. Additionally, this method requires decision makers to remain consistent in making pair wise comparisons among numerous decision criteria. Accurate expression of relative preferences on the criteria is difficult for decision makers due to the limitations of the 9-value scale of Saaty. Herrera-Viedma et al., (2004) proposed the consistent fuzzy preference relations for establishing pair wise comparison preference decision matrices using the so-called additive transitivity property. This method which is based on linear relationship, not only enables decision makers to express their preferences over a set of alternatives with the least judgments, but also avoids checking the consistency in decision-making process. Although Herrera-Viedma et al., (2004) proposed a method to avoid assessing the consistency of pair wise comparisons based on linear relationships, no model exists for improving the consistency of pair wise weighting matrix (PWM) with nonlinear relationships.

2. Research Methodology

In the management literature, each traditional task of a manager such as planning, organizing, control, resource allocation and monitoring is considered as a perspective of decision-making. Decision-making process is a function of critical factors such as objective, time of decision-making and complexity of the decision variables. For designing and implementing the assessment and decision-making model based on the criteria, factors and options, first the major criteria (primary and secondary) of the assessment process are identified with the help of the experts and by means of questionnaires. Then, a new model which is called N_A^3 is proposed for the analysis of the criteria contributing to the ultimate credit client assessment and budget allocation decision-making. In the next step, the factors and parameters affecting the final decision-making are determined and introduced to the system. Then, the expert system is implemented using N_A^3 model results and already identified factors. The next step is devoted to the validation of the expert system where the validity of a number of credit clients is investigated using the assessment model and the expert system. In the end, the results are compared to the real results. Fig illustrates steps of proposed assessment model and expert system.

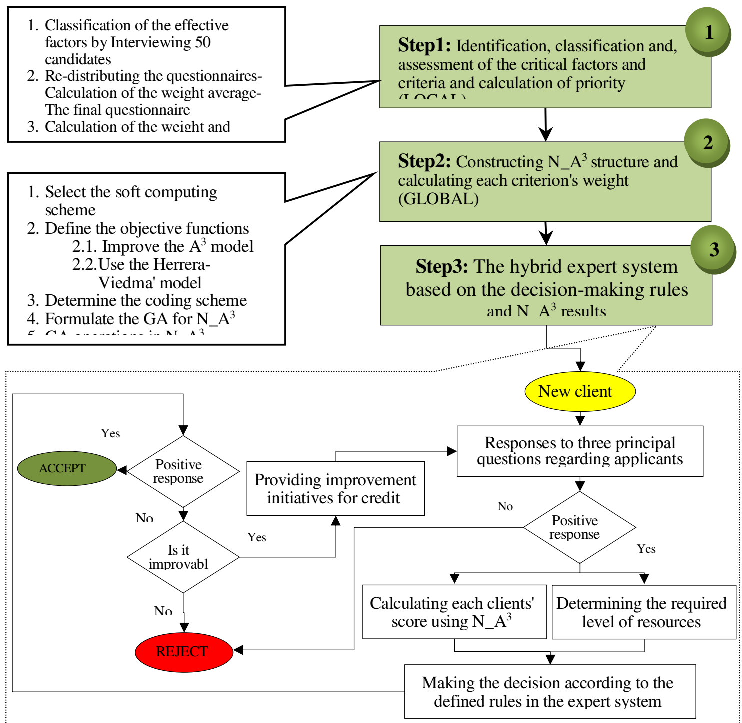

Fig 1. The main steps of the feature selection and client assessment using N_A^3 and expert system

Three steps have been defined as follows:

Step 1: Identification, classification and, assessment of the critical factors and criteria of credit client selection and calculation of priority:

- Interviewing 50 candidates; including bank managers and experts.
- Classification of the effective factors to three levels of "Bank (Bn)", "Industry (In)" and " Firm (Fm)" and preparing client assessment questionnaires by using the experts opinion(50 candidates).
- Distributing the questionnaires among bank managers and experts in order to determine the weight and priority of factors and applying the required modifications such as adding new and similar factors and inter-category criteria movement to the form.
- Calculation of the weight average and standard deviation of the results and applying the required modifications to the questionnaire , then calculation of coefficient of reliability by Cronbach' α (81%).
- Re-distributing the questionnaires among bank managers, and experts in order to determine the weight and priority of the factors along with the earlier determined average and deviation of the previous results.
- Calculation of the weight average and standard deviation of new responses.
- The final questionnaire is again offered to the bank managers and experts for the final weighting and prioritizing of the

criteria along with the previous average and standard deviation.

- Calculation of the weight and priority of each criterion using the weight average (LOCAL)

Step 2: To design the assessment model, all of the criteria and effective factors have been divided into three levels of "Bank (Bn)", "Industry (In)" and "Firm (Fm)" in previous step. This hierarchy has been illustrated in Fig .1. The whole process of designing the assessment model and calculating the weight of every factor, criterion and option is as follows:

- Designing the N_A^3 structure with respect to the identification and classification of the criteria and effective factors that exert influence on the assessment of credit client (Using the Herrera-Viedma' model for improving the A^3 model).
- Constructing the pairwise comparison matrices using the results obtained from the completed questionnaires by the bank managers and experts (LOCAL).
- Calculating each criterion's weight (priority) using the existing N_A^3 rules (GLOBAL).

Step 3: during the designing stage of the expert system based on the decision-making rules, the following decisions have been taken for every credit client for the budget allocation purpose:

- Responses to three principal questions regarding credit client by the head of the department or an expert.
- Calculating each client's score using the obtained results from the bank managers and expert through the N_A^3 assessment model.
- Converting the scores to linguistic term of very poor, poor, fair, good, and excellent.
- Determining the required level of resources for application of credit client based on the type of the applicant.
- Making the decision whether to accept or to reject the application according to the defined rules in the expert system.
- Presenting rejection or acceptance reasons.
- Providing improvement initiatives for credit client
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3. Designing the Assessment Model by Proposing N_A^3

3.1. Feature selection and Calculatin of each Criterion's weights

In order to gain knowledge on the credit client assessment model, in the first step, several interviews are conducted in which the candidates are executive managers, and experts familiar with this context from several banks and financial organizations in Iran. By comparing the obtained information and the conducted studies in these banks and research centers to those of other countries, it was determined that there is no comprehensive and complete model for the budget assessment and allocation for credit client. In the opinion of these managers and experts, lack of documented procedures is the major factor in the selection and adoption of disqualified applicant. In the second step of the research, the candidates were given two separately designed questionnaires for data collection. In the first questionnaire, all the criteria were divided into three layers based on the results of the interviews. By this questionnaire, candidates were asked to determine its significance based on Likert scale. In addition, the experts were asked to add the factors which were not mentioned in the questionnaire. In the second questionnaire, managers obtained a consensus on the factors. Finally, after determining the affecting factors and their importance, the secondary criteria and parameters for detection and assessment of each criterion were identified.

Based on the documents and the conducted interviews with the managers and experts, the factors affecting the credit client assessment process were classified as follows:

1- Bank (Bn) level assessment criteria including those of the Available Bank Budget (Resources), Industry Assessment Criteria, and conformity with bank strategies.
2- Industry (In) level assessment criteria including those of technical feasibility, firm assessment criteria and financial and economic feasibility criteria.
3- Firm (Fm) level assessment criteria including quality criteria, applied criteria and client specifications.

In order to collect the opinions of the managers and experts on the influence of each primary and secondary criteria in the credit client assessments, a questionnaire was designed. This questionnaire contains a comparison table for the primary criteria at bank, industry, and firm levels and five other tables for the comparison of the secondary criteria including technical feasibility, financial and economic feasibility, applied criteria, quality criteria and client specifications. In these tables, the impact of each criterion on the success of a credit client is determined as very poor, poor, fair, good and excellent. Of 160 questionnaires distributed among the banks and financial organization, 132 questionnaires have been completed. The result has been calculated as the weighted average significance given to each criterion in the collected responses. The criteria and their subcategories are presented in Fig .1.

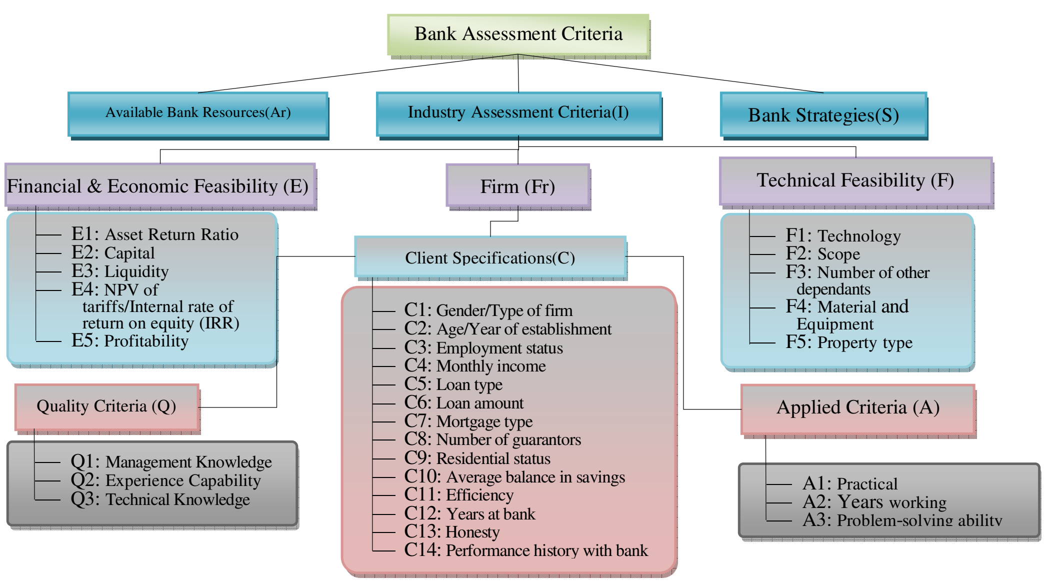

Fig .1 The hierarchy framework for evaluating loan applicants

3.2. Proposed new adaptive AHP approach (N_A^3)

Our world is full of multi-criteria problems which often faces us decision-making problems. For example, in macro decision-making contexts such as allocating the state budget, experts follow different objectives and intend to obtain optimum results. In some cases, the result of the decision-making process is so important that any error may lead to irretrievable consequences. Therefore, it is necessary to use appropriate technique or techniques for optimum choosing and selection of the credit client. One of the most completed techniques is the AHP model developed by Saaty in 1980.

The A^3 model was proposed in 2008 to improve the traditional AHP method of solving MCDM problems from three perspectives: (1) cost effectiveness (2) timeliness and (3) improved decision quality. Although the A^3 provides an automatic mechanism for improving CR, it depends on initial assessment (original PWM). It causes the result of model which is related to subjective view. For overcoming this shortcoming, we improved the A^3 model and integrated with Herrera-Viedma' model and proposed the new adaptive AHP approach (N_A^3). According to Fig 1.five main steps are needed for applying N_A^3, which are briefly discussed here.

Step 1: Select the soft computing

Technique selection depends on the characteristics of the problem field. Lin et al., (2008) used Genetic Algorithm (GA) as the best choice for this method. The GAs, first proposed by Holland (1976), are the algorithms based on the observation of the natural selection in the evolution of natural life. The basic GA mechanism consists of three basic operations: (1) reproduction; (2) crossover; and (3) mutation. For detailed description of GA operations, see Goldberg (1989).

Step 2: Define the objective functions

Lin et al. proposed only two functions in their method having the consistency ratio (CR) and a difference measurement between the adapted PWM and the original PWM (DI). CR is definitely a primary objective value to be minimized and the other objective is required to guide the search toward the direction that reserves the DM's original belief in the relative importance of the various criteria. The difference measurement between the adapted PWM and the original PWM is considered as the second objective. Using only these two functions causes the results to be subjective decision. For overcoming this shortcoming, we proposed the other function as follows:

HI: A difference measurement between the adapted PWM and the HPWM, the PWM which is achieved via Herrera-Viedma' model (More details of this calculations are explained in section 4).

Step 3: Determine the coding scheme

In our proposed model like A^3, the gray code (GC) scheme has been adopted. Because by using GC, three important concerns are considered: (1) the coding scheme should guarantee global search; (2) the coding should be compact; and (3) similar numbers should be coded similarly.

Step 4: Formulate the GA for N_A^3

Since our goal is to determine the values of elements in PWM for eigenvector (the final weights for the various criteria) of the matrix to be found, the considered parameters include all the elements of PWM. The PWM is a positive reciprocal matrix. Thus, only the elements in the upper triangular of PWM are required. The elements on the reciprocal positions can be obtained by $a_{ji}=1/a_{ij}$ where a_{ij} is the element of row *i* and column *j* in PWM. Therefore, only $(n^2-n)/2$ elements are required for constructing PWM. Thus, we can consider $(n^2-n)/2$ elements as the parameters in GA.

Then, an individual gene called genotype in GA for A^3 is built. Each parameter is a chromosome on the genotype. The values of the $(n^2-n)/2$ elements in PWM are coded into GCs. Each digit in GC is either 0 or 1. In addition to the digits for the $(n^2-n)/2$ elements in PWM, four real number parameters should be recorded on each genotype: (1) the maximum eigenvalue of the relative importance weight matrix, (2) the difference index (DI) between the original genotype and the derived genotype, (2) the difference Herrera-Viedma' index (HI) between the original genotype and the HPWM (the PWM which is achieved from Herrera-Viedma' model, (4) the overall index (OI) combining the performance of CR , DI and HI. Since the lower eigenvalue achieves the lower CR, the maximum eigenvalue represents the first objective (i.e., consistency). The DI and HI represent the second and third objective. There are many ways to measure DI such as the Hamming distance between the two genotypes or the summation of square differences of all elements between the two genotypes and two PWMS. The DI and HI are defined As $((\lvert G./G^{*}\rvert + \lvert G./G^{*}\rvert)/(n^2-n))$.Where G and G^* are row vectors of the original and derived genotypes or PWMs in the real number format. In this equation, "./" means element-to-element division. That is, the division is performed for each pair of elements at the same position in the two genotypes or PWMs. The last parameter in the genotype is an overall evaluation of the three objectives. It is obvious that the goal of N_A^3 be to reduce the values of DI, HI and OI. The lower value of the first objective means the better consistency. The lower value of the second objective means better conformity between the derived PWM and DM's original belief as subjective issue and lower HI guaranty better conformity between the derived PWM and the HPWM (the PWM which is achieved from Herrera-Viedma' model) as objective issue. Thus, a straightforward definition for OI is simply the summation of λ_{max}, DI and HI. Since the lowest value of λ_{max} is *n* (number of criteria) and the lowest value of DI and HI are unit (when two genotypes or PWM are identical), it is intuitive to define OI as shown OI= $(\lambda_{max}-n)+(DI-1)+(HI-1)$. In the data structure of a genotype, there are totally $[((n^2-n)/2)+4]$ elements. The first $(n^2-n/2)$ elements are in GC format (i.e., 0 or 1). The last four elements are λ_{max}, DI and HI.

Step 5: GA operations in N_A^3

A primary genotype is created by the upper-right triangle of the initial PWM. In this paper, we use the GA operations proposed by Lin et al. According to Lin et al., (2008), the primary genotype should reproduce 20 times to generate 20 identical genotypes. Next, mutation should be applied to all genotypes except 1. This mutation results in an initial population with only 1 genotype that is identical to the original genotype; the other 19 genotypes are slightly different from the original genotype. During the second step, the initial population should cross over with itself to generate 400 (20×20) off-springs. Only 1 outcome g is the identical to the original genotype and 399 new genotypes are produced. All 400 genotypes are evaluated and the best 20 genotypes are selected for further evolution. The evolution process stops when all genotypes are the same or the objective performances do not improve any more. Then, the genotype with the best objective performance is selected as the final genotype. The PWM is then constructed based on the final genotype and the eigenvector of the PWM is found to be the final weights for the various criteria.

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4. Model development and experimental details

A real world decision-making problem in ranking of credit customer for a case project (a large bank in Iran) is adopted as a case study. In this problem, the proposed N_$A^3$are applied for ranking of credit customers of the large bank of Iran.

4.1. Experimental details of proposed model (N_A^3)

Step 1: Data Collection

Collecting the expert judgment for running N_A^3 model is very important. For applying the N_A^3 model, we must apply two kinds of questionnaires to determine the criteria weightings. The committee consists of 15 experts including managers and experts from credit department of the bank. They must determine the five level MCDM criteria. According to Fig .1, this MCDM hierarchy contained three level-one criteria including available bank resources, industry assessment criteria, and bank strategies. Moreover, three level-one criteria were further broken down into sub-criteria. The Industry assessment level-one criterion was also broken down into three level-two criteria, namely: financial & economic feasibility (E), firm, and technical feasibility (F). All level-two criteria were also broken down into three level-three criteria. Similarity these levels are expanded to five levels according to Fig .1. Subsequently, the committee should determine the weightings of the criteria for each level of the MCDM hierarchy. The committee then should assign each bidder a score for each criterion. The overall score of a bidder is calculated by aggregating the weighted score of each criterion from the bottom level to the top level. A five-point Likert scale ranging from 1 to 5 is used to assess the scores at the bottom level. The committee of decision makers has completed two kinds of questionnaires which have been designed for measuring the weight of the criteria being illustrated in Fig .1. The first questionnaire is similar to the questionnaire which Lin et al., have used in A^3 model. The other questionnaire is related to Herrera' model.

The model proposed model by Herrera-Viedma in 2004 helps the DM to express easily his or her opinion in a short time. A special questionnaire which Wang et al., (2007) has proposed was used to complete a pairwise comparison matrix.

Step2: Calculating the weights of the criteria (the first calculations)

After collecting data by two kinds of questionnaire in this step, the score of every elements of PWM must be calculated. In the first questionnaire, every DM must determine the values of the elements in the upper triangular of PWM (n^2-n/2). But in the Herrera' model, every DM must determine the values of the (n-1) elements and other elements are calculated by Eq1 to Eq4. For instance, 5 judgments of decision makers for a set of five adjoining factors {F1.F2, F2.F3, and F3.F4} are listed as follows for technical feasibility (F) criteria (

Table 1):

Table 1. The judgment scores for five criteria evaluated by five decision makers

	DM1	DM2	DM3	DM4	DM5	
F1	4:1	3:1	1:1	2:1	1:1	F2
F2	1:2	1:4	1:2	1:3	1:1	F3
F3	1:3	1:4	1:3	1:4	1:2	F4
F4	1:5	1:5	1:4	1:5	1:5	F5

DM: (Decision maker)

According to Table 1, every DM must fill only 4 cells. The DM must compare 2 factors with each other. In this stage, the DM should ask himself/herself this question and answer it by 5 scales.

The following table illustrates the steps for calculating factors' weight based on Herrera-Viedma' model (2004) after collecting the opinions. To illustrate these steps, the assessment of decision maker 1 is selected as an example here.

1- Table 2 is the pairwise comparison matrix of decision maker 1 which shows the importance of each of two adjoining factor for a set of n - 1 preference values.

Table 2. First step of pairwise comparison matrix of decision maker 1

	E1	**E2**	**E3**	**E4**	**E5**
E1	1	4.00	x	x	x
E2	x	1	0.50	x	x
E3	x	x	1	0.33	x
E4	x	x	x	1	0.20
E5	x	x	x	x	1

2- In this step, the elements are transformed into an interval [0, 1] by equation 1 in which $a_{ij} \in [1:5,5]$ and $W_{ij} \in [0,1]$.

$$W_{ij} = (1/2)(1 + \log_5 a_{ij}) \qquad (1)$$

where W_{ij} indicates the lack of indifference between factors i and j, $W_{ij} = 1$ suggests that factor i is absolutely more important than the factor j, $W_{ij} = 0$ denotes that factor i is absolutely less important than the factor j, and $W_{ij} > \frac{1}{2}$ reveals that the factor i is preferred to factor j.

3- To calculate the remaining elements, equation's 2 and 3 are used.

$$W_{ij} + W_{ji} = 1 \qquad \forall i, j \in \{1, \ldots, 5\} \qquad (2)$$

$$W_{ji} = ((j-i+1)/2) - W_{i(i+1)} - W_{(i+1)(i+2)} - W_{(i+2)(i+3)} - \ldots - W_{(j-1)j} \qquad (3)$$

4- If this preference matrix contains any values that are not included in the interval [0,1], but in an interval [-a,1 + a], then a transformation function is required to preserve the reciprocity and additive transitivity. The transformation function is given by equation 4 where a indicates the absolute value of the minimum in this preference matrix.

$$f(W_{ij}) = w_{ij} = (W_{ij} + a)/(1 + 2a) \qquad (4)$$

۵- Final weight is achieved by using the average of the normalized matrix row. The normalized matrix and final priority of influential factors for decision maker 1 are shown in

6- Table 3 .

Table 3. Normalized weight matrix and priority of influential factors

	E1	E2	E3	E4	E5	Priority	Rank
E1	0.196	0.197	0.197	0.196	0.191	0.195	3
E2	0.116	0.140	0.130	0.105	0.000	0.098	5
E3	0.156	0.169	0.163	0.150	0.095	0.147	4
E4	0.219	0.214	0.216	0.222	0.246	0.224	2
E5	0.312	0.280	0.294	0.327	0.468	0.336	1

7- The above stage is applied for calculating other decision makers' matrix too.

Now, we have the pairs of 120 comparison matrices with two kind of questionnaires (Each DM was required to complete 8 relative importance assessment tables, and thus generated eight PWMs, including one level-one PWM, one level-two PWMs, two level-three PWMs, two level-four PWMs, and two level-five PWMs. Totally, 120 (=8×15) PWMs were obtained from two kind of Herrera-Viedma' questionnaires model and A^3 questionnaires). In the next section, the details of second questionnaire results are explained.

Step3: Experimental details of N_A^3 model (the second calculation)

In the previous step, the relative importance among criteria at the same level is compared to obtain PWMs using the discrete 5-value scale of Saaty. Fifteen managements and experts of credit department joined in assessing elements weightings in the case study. And finally, the pairs of 120 PWMs is prepared for using in this step.

A prototype computer program was designed with the MATLAB language for implementing the proposed A^3. The

Table 4 displays the average criteria weightings and shows the average CR, DI, HI and OI values using the N_A^3.

Table 4. The average of weightings, CR, DI and OI values obtained using N_A3 approaches

	Level one		Level two		Level three		Level four		Level five	
	Local	Global	Local	Global	Local	Global	Local	Global	Local	Global
Ar	0.143	0.286								
I	.632	0.422								
S	0.225	0.293								
E			0.273	0.391						
Fr			0.291	0.293						
F			0.436	0.316						
C					0.592	0.421				
E1					0.178	0.063				
E2					0.202	0.113				

E3					0.147	0.043				
E4					0.134	0.038				
E5					0.339	0.134				
F1					0.121	0.030				
F2					0.198	0.076				
F3					0.148	0.040				
F4					0.186	0.059				
F5					0.347	0.112				
Q							.254	0.319		
A							0.154	0.260		
C1							0.013	0.004		
C2							0.024	0.008		
C3							0.048	0.018		
C4							0.106	0.034		
C5							0.093	0.043		
C6							0.061	0.031		
C7							0.146	0.051		
C8							0.042	0.022		
C9							0.057	0.019		
C10							0.062	0.027		
C11							0.071	0.024		
C12							0.031	0.013		
C13							0.172	0.060		
C14							0.074	0.067		
Q1									.210	0.077
Q2									0.280	0.113
Q3									0.510	0.129
A1									0.311	0.079
A2									0.392	0.134
A3									0.297	0.047
Weighting approach										
Assessment cycle		Primitive	Final							
No. of PWM		120	41							
Average CR		1.72	0.082							
Average DI		1	1.15							
Average HI		1.02	1.12							
Average OI		0.76	0.61							

Step4: Knowledge base and Inference motor

In parallel with the goal of this paper which is designing the expert system for assessing and evaluating loan applicant, in this section, the final decision is made after the assessment of expert system. This decision is made based on the following factors:

The knowledge base of an expert system is a set of decision-making rules and, therefore, one of the major problems of rule-based expert systems is the numerousness rules required for decision-making. In this study, the number of the rules has dramatically reduced due to the application of N_A^3. It has occurred in a

Rule01 :	if Strategy = (VP or P)	then	Reject
Rule02 :	if Resource = (VP or P)	then	Reject G, E, P, VP
Rule03 :	if Resource = (F)	then	Reject F, P, VP
Rule04 :	if Assessment(Bn, In, Fm) = (VP or P)	then	Reject
Rule05 :	if Experience = (VP or P)	then	Reject
Rule06 :	if Assessment E = (VP or P)	then	Reject
Rule07 :	if Assessment F = (VP or P)	then	Reject
Rule08 :	if Assessment C = (VP or P)	then	Reject
Rule09 :	if Assessment S = (VP or P)	then	Reject
Rule10 :	if Assessmen Q = (VP or P)	then	Reject

In this system, first, the credit clients or applicant that are disqualified for execution are rejected based on the expert system rules and, then, decision-making is done for the rest of the applicants as follows:

1- If the score of applicant is Excellent, then it is accepted.
2- If the score of applicant is good, then it is accepted based on terms.

The terms of the budget allocation for these applicants is to increase the certainty of the applicant situation or reduce the bank center risk. Some measures may be taken in line with it as to increase the accuracy of the progress reports and to decrease the bank share of investments.

3- If the score of applicant is fair, then it is prioritized as the second level for the budget allocation.

1- The results obtained from N_A^3
2- Available resources
3- Existing rules of the expert system

manner that while more than 5000 rules where required for the expert system prior to the application of N_A^3 with respect to the total number of the identified criteria; it was reduced to 50 rules by applying ANP.

Regardless of other factors, some of the principal rules affecting the final decision are as follows:

The terms of the budget allocation to these applications is to support the promotion of the conditions set by the bank to the first level. The expert system proposes prioritized solutions and initiatives by comparing these applications with ideal applicant conditions.

5. Final decision Making Engine

This system is implemented through three steps illustrated as Fig .2.

In the first step, the head of the group or the center is asked three questions:

- Does the application comply with bank conditions and restrictions?
- Do the applicants have qualifications and permission for the implementation?
- Does the application provide the initial and legal terms for the budget allocation?

If the answers to all three questions are positive, the system grants access to the second step. Otherwise, a rejection notice is issued.

In the second step, the managers and experts are asked 39 questions. After choosing the appropriate option for each criterion, the system calculates the final score and the application acceptance percentage based on the chosen options and N_A^3 rules. Then, it goes to the decision-making steps.

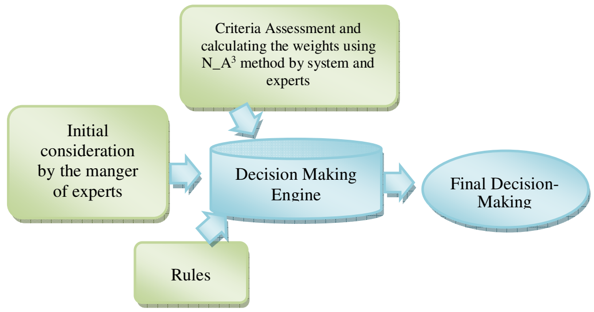

Fig .2 The final decision making engine

In the third step, the final decision is made by the inference motor based on the existing rules of the knowledge base. The output of the system includes the final decision-making result, advantages and disadvantages of the application, and the bank terms for the improvement of the second type application.

6. System Validation

Validation of the expert system is an important part of the system development effort in order to ensure the correct performance and consistent results. The validation method mentioned here is applicable to real and generated data. The system has been put to test by comparing the real world results and the previous opinions of the assessors with the obtained results from the system for 200 applications. The generated input data for each application was obtained from the assessors of those applications. A comparison between the results obtained from the expert system and the real assessments show a successful level of 95%. In case of 200 evaluated applications, the assessment results for 190 applications were consistent with real life results. The detail of system validation is described as follow (

Table 5).

Table 5: The result of using historical data for system validation.

The method for validity	Number of application	No. Accepted	No. Rejected	No. Accepted	No. Rejected
		by annual assessment		by proposed expert system	
Using historical data	200	73	127	67	133
Error %	The result of 6 applications which assess by Proposed expert system is not matched by real result therefore the error % is 5%				

7. Summary and Conclusion

In this study, an assessment model and the expert system were developed through the identification of principal criteria and factors that affect the success of an application of credit client. The affecting criteria comprise 39 items classified in five levels. These criteria include information such as technical feasibility criteria, financial and economic criteria, client specifications, quality criteria, and applied criteria.

In order to determine the priority and influence of each criterion on decision-making and assessment, the N_A^3 method has been used with respect to the five criteria's. The results show that from assessors' points of view, the affecting factors in the assessment have the sequence priority of client specifications, financial & economic feasibility, technical feasibility, applied criteria, and quality criteria. The second part of the proposed model is devoted to the final decision-making on the budget allocation. Although the process of assessment and identifying the criteria are very important and influencing in the loan process, other parameters also exert influence on the final decision including available resource, and conformity with bank strategies. The final decision regarding the budget allocation and client assessment is made considering the status of the criteria and the assessment results. Various conditions resulting from these factors are dealt with and implemented under this rule-based expert system. The validation of the model shows that if valid data are fed into the system, it will yield acceptable results. The use of this method includes such advantages such as reduction in the number of rules, increase in calculation speed and accuracy, reduction in decision-making time, intra-category application prioritization, reduction in system complexity, and considering multiple objectives. For example the proposed model causes decreasing decision-making time. In second step of proposed model, the number of calculations is reduced. In the first level, DMs must compare every three factors with each other and rate them by 5-value scale which it makes one PWM. In the second level, DMs must complete one PWM. Similarly in third, fourth and fifth level they must complete two PWM in each level. Totally, $120=15\times(1+1+2+2+2)$ PWMs were obtained. Among the 120 PWMs, only 56 PWMs were acceptable (i.e., $CR<0.10$) at the first assessment; the rest of 64 PWMs required reassessment. In the N_A^3 weightings, the primitive PWMs obtained from the first assessment of the AHP weightings is automatically reassessed when CR exceeds 0.10. In the case study, 64 (out of 120) PWMs were unacceptable (that is, CRs >0.10). Thus, the proposed N_A^3 is applied to adjust the relative importance values of the criteria in the unacceptable PWMs to meet the consistency requirement. Therefore, calculation number reduction due to saving time is visible.

Results showed that N_A^3 provides the results that are more accurate and have the most important ability of proposed method which is related to objective and subjective view in decision-making process, while in A^3 method only subjective view is noticed.

7.1. Limitations and Suggestions for future research

Despite, several benefit of N_A^3 in measuring the priority of credit industry sections, there are limitations which should be removed and it can be considered by other researches. One of the limitations is that the N_A^3 is limited to crisp evaluation, and fuzzy approaches can be explored in future investigations while using opinion of expert and questionnaires. Neglecting the non-linear relationships, as well as the uncertainty of financial and economic criteria are other limitations of the model which is proposed for future investigations.

Acknowledgement

We highly appreciate the management of Export Development Bank of Iran (EDBI) for their technical support of this research.

References

[1] Abdou, H., Pointon, J. and El-Masry, A., 2008. Neural nets versus conventional techniques in credit scoring in Egyptian banking. *Expert Systems with Applications*, *35*(3), pp.1275-1292.

[2] Abdou, H.A., 2009. Genetic programming for credit scoring: The case of Egyptian public sector banks. *Expert Systems with Applications*, *36*(9), pp.11402-11417.

[3] Aliheidari Bioki, T., Khademi Zare, H., Finding a new integrated approach for ranking of bank credit customer based on A2-DEA, 6th International Conference of Iranian Operations Research Society, May 8-9, 2013.

[4] Chen, Y.S., 2012. Classifying credit ratings for Asian banks using integrating feature selection and the CPDA-based rough sets approach. *Knowledge-Based Systems*, *26*, pp.259-270.

[5] Chi, B.W. and Hsu, C.C., 2012. A hybrid approach to integrate genetic algorithm into dual scoring model in enhancing the performance of credit scoring model. *Expert Systems with Applications*, *39*(3), pp.2650-2661.

[6] Chin, K.S., Xu, D.L., Yang, J.B. and Lam, J.P.K., 2008. Group-based ER–AHP system for product project screening. *Expert Systems with Applications*, *35*(4), pp.1909-1929.

[7] Cui, B. and Han, R., 2008, June. Modeling of dimensional errors in slender bar turning using artificial neural networks. In *Intelligent Control and Automation, 2008. WCICA 2008. 7th World Congress on* (pp. 6053-6056). IEEE.

[8] Dinh, T.H.T. and Kleimeier, S., 2007. A credit scoring model for Vietnam's retail banking market. *International Review of Financial Analysis*, *16*(5), pp.471-495.

[9] Belew, R. and Lashon, B., 1991. Genetic Algorithm in Search, Optimization, and Machine Learning.

[10] Gönen, G.B., Gönen, M. and Gürgen, F., 2012. Probabilistic and discriminative group-wise feature selection methods for credit risk analysis. *Expert Systems with Applications*, *39*(14), pp.11709-11717.

[11] Herrera-Viedma, E., Herrera, F., Chiclana, F. and Luque, M., 2004. Some issues on consistency of fuzzy preference relations. *European journal of operational research*, *154*(1), pp.98-109.

[12] Holland, J.H., 1976. Adaptation in natural and artificial systems. An introductory analysis with application to biology, control, and artificial intelligence. *Ann Arbor, MI: University of Michigan Press*.

[13] Huang, C.C., Chu, P.Y. and Chiang, Y.H., 2008. A fuzzy AHP application in government-sponsored R&D project selection. *Omega*, *36*(6), pp.1038-1052.

[14] Kokangul, A. and Susuz, Z., 2009. Integrated analytical hierarch process and mathematical programming to supplier selection problem with quantity discount. *Applied mathematical modelling*, *33*(3), pp.1417-1429.

[15] Lin, C.C., Wang, W.C. and Yu, W.D., 2008. Improving AHP for construction with an adaptive AHP approach (A 3). *Automation in construction*, *17*(2), pp.180-187.

[16] Lorie, J.H. and Savage, L.J., 1955. Three problems in rationing capital. *The Journal of Business*, *28*(4), pp.229-239.

[17] Mahmudi, J., Nalchigar, S. and Ebrahimi, S.B., 2009. Two DEA Models Employment in IS Project Selection for Iran Ministry of Commerce. *International Journal of Industrial Engineering*, *20*, pp.77-81.

[18] Marshall, A., Tang, L. and Milne, A., 2010. Variable reduction, sample selection bias and bank retail credit scoring. *Journal of Empirical Finance*, *17*(3), pp.501-512.

[19] Ngai, E.W. and Chan, E.W.C., 2005. Evaluation of knowledge management tools using AHP. *Expert systems with applications*, *29*(4), pp.889-899.

[20] Saaty, T.L., The Analytic Hierarchy Process, McGraw-Hill, New York, 1980. *There is no corresponding record for this reference*.

[21] Seyedhoseini, S.M., & M. Hatefi, A., An Integrated Risk-Based Technique for Project Plan Selection, *International Journal of Industrial Engineering,* Vol 20, No.1,2, 2009, pp. 31-40.

[22] Shen, C.H., Huang, Y.L. and Hasan, I., 2012. Asymmetric benchmarking in bank credit rating. *Journal of International Financial Markets, Institutions and Money*, *22*(1), pp.171-193.

[23] Tam, C.M., Tong, T.K. and Chiu, G.W., 2006. Comparing non-structural fuzzy decision support system and analytical hierarchy process in decision-making for construction problems. *European Journal of Operational Research*, *174*(2), pp.1317-1324.

[24] Tang, Y.C. and Beynon, M.J., 2005. Application and development of a fuzzy analytic hierarchy process within a capital investment study. *Journal of Economics and Management*, *1*(2), pp.207-230.

[25] . Wang, J., Hedar, A.R., Wang, S. and Ma, J., 2012. Rough set and scatter search metaheuristic based feature selection for credit scoring. *Expert Systems with Applications*, *39*(6), pp.6123-6128.

[26] Wang, T.C. and Chang, T.H., 2007. Forecasting the probability of successful knowledge management by consistent fuzzy preference relations. *Expert Systems with Applications*, *32*(3), pp.801-813.

[27] Wey, W.M., 2005. An integrated expert system/operations research approach for the optimization of waste incinerator siting problems. *Knowledge-Based Systems*, *18*(6), pp.267-278.

طراحی یک ابزار تصمیم گیری جدید به منظور انتخاب معیارها و ارزیابی مشتریان اعتباری

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تاریخ دریافت: ۹٤/۲/۲۵ تاریخ پذیرش: ۹٤/۱۲/۲۸

در این مطالعه یک یک مدل ارزیابی به منظور انتخاب معیارها و اعتبار سنجی مشتریان متقاضی تسهیلات بانکی طراحی و ارائه شده است. مدل پیشنهادی یک مساله تصمیم گیری چندمعیاره است که شامل معیارهای زیادی است. مهمترین نوآوری این تحقیق طراحی مدلی جدید جهت انتخاب معیارها و ارزیابی اعتباری با استفاده از ترکیبی از روش توسعه یافته تحلیل سلسه مراتبی و الگوریتم ژنتیک می باشد. در این مقاله علاوه بر معیارهای کمی، معیارهای کیفی نیز در نظر گرفته شده است. روش تحلیل سلسه مراتبی یکی از روش های بسیار پرکاربرد در زمینه حل مسایل تصمیم گیری چند معیاره می باشد. در سال ۲۰۰۸ لین و همکارانش یک مدل جدید به نام A^3 برای توسعه این روش ارائه نموده اند به طوریکه تعداد مراحل محاسبه نرخ سازگاری را کاهش داد. در این مقاله یک روش جدید با نام N_A^3 به منظور ساخت مدل ارزیابی اعتباری ارائه شده است. نتایج اجرای مدل پیشنهاد شده نشان داد که مدل ضمن کاهش محاسبات و افزایش سرعت عملیات تصمیم گیری، باعث بهبود روش موجود می‌شود.

واژگان کلیدی: N_A^3، انتخاب معیار ارزیابی، ارزیابی اعتباری، بانکداری

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