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A Credit Rating Model in a Fuzzy Inference System Environment

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Abstract: One of the most important functions of an export credit agency (ECA) is to act as an intermediary between national governments and exporters. These organizations provide financing to reduce the political and commercial risks in international trade. The agents assess the buyers based on financial and non-financial indicators to determine whether it is advisable to grant them credit. Because many of these indicators are qualitative and inherently linguistically ambiguous, the agents must make decisions in uncertain environments. Therefore, to make the most accurate decision possible, they often utilize fuzzy inference systems. The purpose of this research was to design a credit rating model in an uncertain environment using the fuzzy inference system (FIS). In this research, we used suitable variables of agency ratings from previous studies and then screened them via the Delphi method. Finally, we created a credit rating model using these variables and FIS including related IF-THEN rules which can be applied in a practical setting.

Keywords: credit rating; export credit agencies; uncertainty environment; fuzzy inference system; Delphi method

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1. Introduction

Due to the strong expansion of international trade, many countries have established export credit agencies (ECAs) to protect exporters from bankruptcy due to political and commercial risks. Their agents evaluate foreign buyers and determine whether to grant credit to these exporters to protect them from risks. The agents evaluate the buyers based on their countries' sovereign credit. In this paper, we use a Fuzzy Inference System (FIS) to evaluate exporters' credit in an uncertain environment.

For each contract, the sellers need to know about the financial situation of the buyers. This study helps them to evaluate the ability of buyers to repay their debt, and to determine the probability of default. There are two types of credit ratings: (1) sovereign credit rating and (2) corporate credit rating. To ascertain the risk level of the buyers' investment, we evaluate them as well as their government. Credit risk can be analyzed using various financial tools, which are affected by political, social, and economic factors.

Decision-making is an essential function of any enterprise. It is very difficult for decision makers (DMs) to utilize quantitative variables since many evaluation attributes are vague. For this type of uncertain environment, linguistic and verbal scales can be helpful in making an appropriate decision. Thus, the fuzzy set theory of linguistic variables can express the preferences of decision makers in an uncertain environment.

Fuzzy logic and fuzzy set theory, introduced independently by Zadeh [1] and Klaua, have inspired many scholars over the decades. Since then, fuzzy models have found wide areas of application, including various economically important areas. For instance, in [2], an adaptive neuro-fuzzy inference system was used for selecting vehicle routes under uncertainty conditions. In [3], a similar type of model was used for determining economic order quantities (such as for procurement or production planning). Based on the Boston Consulting Group (BCG) portfolio matrix, a neuro-fuzzy approach is elaborated in [4] for analyzing human resources. Further application examples include the multiobjective route planning for the transport of hazardous material [5] or location planning for city logistics [6].

In addition, many studies have been published on using fuzzy modelling in the context of buyer evaluation and credit scoring, including those by Akkoç [7] who investigated loan defaults. Due to financial crises, many financial institutes aim for accurate credit scoring models. Ramkumar and Busi [8] utilized a modified analytic network process (ANP) and fuzzy inference system to establish a risk assessment model for third-party e-procurement systems. As part of a modified ANP, decision makers are encouraged to express their preferences verbally rather than via a numerical rating system. Yazdi et al. [9] used an adaptive neural fuzzy inference system to create inputs, outputs, membership functions, and fuzzy rules. The results indicated that these sets of constraints lead to similar constraint categories with output fuzzy trained systems. Moghadam et al. [10] used the FIS method to map the model. They found that a fuzzy inference system could be helpful in this type of research. The results showed that two factors were particularly effective for mapping via FIS. In the first step, FIS was used to weight factors. In the next step, the factors were integrated using FIS, and the final step revealed the results of exploratory boreholes. Dash and Dash [11] tested a model to predict stock prices by using the Self-Evolving Recurrent Neuro-Fuzzy Inference System (SERNFIS) and modified differential harmony search. They used stock market time series data utilizing diverse time frames. The Takagi–Sugeno–Kang (TSK) model and fuzzy IF-THEN rules were also used.

In order to evaluate buyers who represent companies or individuals, these agencies must consider some of the following indicators or use models created by credit rating agencies such as Moody's, S&P, Fitch, Capital Intelligence, Euler Hermes, Japan Credit Rating Agency, etc. [12]. For example, the Export Guarantee Fund of Iran (EGFI) is the only credit rating agency that uses a customized model to evaluate the credit ratings of buyers' companies to determine whether to grant credit to exporters (EGFI website). Considering that this agency uses both quantitative and qualitative indicators for evaluating these companies, it is of utmost importance to create the most accurate model possible. Furthermore, because the economic situation of Iran is uncertain, using a model for translating ambiguous and qualitative indicators is crucial to obtaining the most accurate assessment [13]. A fuzzy inference system is a robust computerized technique for decision-making in such an environment.

For this study, a three-stage hybrid adaptive neuro-fuzzy inference system for credit scoring was used as a statistical technique. This model was tested in Turkey's national banks using a 10-fold cross process [7]. The results revealed that this model performed better than linear discriminate analysis, logistic regression analysis, and an artificial neural network. The contributions this study makes are the use of the fuzzy inference system to evaluate credit ratings in uncertain environments. Moreover, our methodology includes building the proposed model by finding a similar one, which most accurately represents the challenging economic situation in Iran. This model is customized via the Delphi method using experts' opinions [7].

In this paper, we present the application of fuzzy modeling methods to a problem of rating companies with respect to credit decisions. Based on the input from experts of a rating agency, ranking criteria are determined and assessed in terms of linguistic variables. Subsequently, fuzzy rules for an FIS are determined. The approach is applied under practical conditions by an ECA in order to cope better with difficult economic conditions and severe budget limitations. In particular, decisions are based on a transparent model instead of ad hoc assumptions and decisions which affect the quality of decisions.

This paper is organized as follows: Section 2 is the literature review. Section 3 presents the research methodology. Section 4 describes the data analysis. Finally, Section 5 presents the conclusions and formulates suggestions for future research.

2. Literature Review and Basic Definitions

2.1. Literature Review

Since the establishment of ECAs, bankruptcy due to political and commercial risks has decreased dramatically. While the ECAs are designed to protect exporters, they are also beneficial to global trade and succeed in encouraging companies to establish more credit. However, because the worldwide economic situation is unstable, making a truly accurate decision is very difficult. To accomplish this, many scholars have studied the credit ratings of companies in uncertain environments. For instance, Al-Najjar and Al-Najjar [14] showed how to measure corporate credit ratings in emerging markets. They used a neural network and a clustering method to rate major companies in Jordan during 2000 to 2007. Bian [15] looked at how the Chinese credit rating agencies were developed. He argued that Chinese companies should have a customized model for evaluating various companies and that they must focus on transparency. Chen and Cheng [16] established a hybrid model for credit rating by employing the rough set theory in an uncertain environment using factor analysis. Then, they used a learning algorithm for establishing decision-making rules. The result showed that this hybrid model was more effective than previous models. Doumpos et al. [17] used a multiple attribute decision-making (MADM) method based on linear programming and structural data to rate European firms using accounting data. Gibilaro and Mattarocci [18] investigated how rating agencies can grant credit based on customers' portfolios. They analyzed 20,389 companies using the S&P, Moody's, and Fitch agencies. They evaluated these companies via the Herfindahl–Hirschman index and customer lifetime value. Gogas et al. [19] showed how to calculate the credit rating of banks. They evaluated 94 American banks by logic probability regression. The results showed that only 84% of those bank ratings were accurate. Orsenigo and Vercellis [20] used linear and nonlinear techniques to determine credit ratings for banks. They used double-bounded tree-connected Isomaps and principal component analysis to assess European, American, and Asian banks; they then classified the banks based on financial and non-financial indicators. Ozturk et al. [21] applied artificial intelligence techniques, such as classification and regression trees, multilayer perception, and support vector machines to measure sovereign credit ratings. Pasricha et al. [22] used Markov regenerative processes to establish a credit rating model. They applied the technique to find matrices of migration probability. They showed how past and current data influenced the ratings. Hu and Hu [23] studied the effect of sovereign ratings on bank stock returns in the European Union. They found that positive sovereign ratings did not lead to a bank's stock price reaction; however, negative events caused negative sovereign rating events.

2.2. Fuzzy Inference System

One of the advantages of fuzzy sets is their ability to translate qualitative and vague information into deterministic and quantitative data. This method has been applied in many different industries worldwide in spite of some conflicting opinions about its methodology [1]. The most common application of this method is decision-making, especially in an uncertain environment. To implement this method, we introduce the definition and notation of sets below. The first definition related to the membership function is as follows:

Definition 1. Fuzzy membership: μ_A is defined as a membership function or characteristic function with values $\mu_A((x) \in [0; 1]$ for $x \in X$. If $A \subseteq X$ indicates a crisp (traditional) set, then μ_A assigns a value 0 or 1 to each member of X. $\mu_A(x) = 1$ if $x \in A$; this means that x has full membership. $\mu_A(X) = 0$ if $x \notin A$; this means that X does not have any membership in X [1].

The membership function of $\widetilde{\mathrm{A}}$ can be specified, for instance, as a triangular, a trapezoidal, a Gaussian function, or a sigmoid function. Moreover, logical operations can be used including AND, OR, and NOT [24].

Definition 2. Triangular fuzzy numbers: $\widetilde{\mathrm{A}} = \left\{\mathrm{x}, \mu_{\widetilde{\mathrm{A}}} | \mathrm{x} \in \mathrm{X}\right\}$. There are three parameters of a triangular fuzzy membership function, a, m, and b. The corresponding function is defined in Equation (1) [1]:

$$\mu_{\widetilde{A}}(x) = \begin{cases} \frac{x-a}{m-a}, & a \leq x \leq m \\ \frac{b-x}{b-m}, & m \leq x \leq b \\ 0, & otherwise \end{cases} \tag{1}$$

The third definition relates to the product of fuzzy numbers based on a t-norm operator.

Definition 3. The product of fuzzy numbers: The fuzzy numbers of $\widetilde{\mathrm{A}}$ and $\widetilde{\mathrm{B}}$ are produced by t-norm operators, as shown in Equation (2) [1]:

$$\mu_{\widetilde{\mathrm{A}}}(\mathrm{x}) \text{ AND } \mu_{\widetilde{\mathrm{B}}}(\mathrm{y}) = -\mu_{\widetilde{\mathrm{A}}}(\mathrm{x}) \times \mu_{\widetilde{\mathrm{B}}}(\mathrm{y}) \tag{2}$$

Based on this method, one of the most important applications is the fuzzy inference system (FIS), which uses IF-THEN rules based on fuzzy membership functions. In FIS, all inputs based on a membership function change to an output membership function according to IF-THEN rules. There are various systems that translate the inputs to output membership functions in the FIS. However, we discuss only the two most essential [25–27]. Mamdani's output membership function is based on defuzzification. After computation with fuzzy numbers, these numbers must be transferred into crisp numbers to make decisions easier. There are many methods available for this. In our study, we use the mean method for changing fuzzy numbers to crisp numbers.

The FIS consists of four steps. First, the inputs and their degree of fuzziness are defined. Second, we set up some fuzzy operators. Third, we determine the weights of each IF-THEN rule and use them to obtain the decision. Fourth, all rules are entered either as inputs or operators.

3. Research Methodology

Because research on export credit agencies is rather novel, there is plenty of scope for study. In this study, we attempt to introduce a new method for credit rating agencies based on the Moody method. It is customized for the Export Guarantee Fund of Iran (EGFI). The research questions are as follows:

1. Which variables are suitable for the EGFI as well as for other credit rating agencies?
2. How does the uncertain environment affect these variables?

In order to determine the variables for determining credit ratings, we introduced Moody's model and experts' opinions on these variables. These variables are interest coverage ratio, current ratio, quick ratio, ownership structure, country risk and so on. After extracting these variables, we evaluated them using the Delphi method as follows:

(a) These variables were sent to the experts of the EGFI to determine which ones were suitable for credit rating agencies.
(b) Within the Delphi method, a 5-point Likert scale was used.
(c) When the average of the experts' opinions was less than 4, this variable was eliminated.

Tables 1 and 2 show the computation of variables and their extractions. The results show that, among 23 variables, only 19 should be used for ranking companies.

Table 1. Preferences of experts (decision makers (DM)) regarding input variables. DEBT-TO-EQUITY RATIO (Earnings Before Interest, Taxes, Depreciation and Amortization(EBITDA)), Debt-Service Coverage Ratio (DSCR), Return On Equity (ROE), Definitions of these input variables are provided in Table 3.

VARIABLES	DM1	DM2	DM3	DM4	DM5	DM6	DM7	DM8	DM9
DEBT-TO-EQUITY RATIO	4	5	4	5	3	4	5	5	4
DEBT RATIO TO EBITDA	5	5	5	4	3	4	5	5	4
DSCR	5	4	4	5	5	5	5	4	3
INTEREST COVERAGE RATIO	3	4	5	5	5	4	5	4	5
CASH FROM OPERATING ACTIVITIES RATIO TO TOTAL SALES	5	5	5	5	4	5	3	5	4
ROE	4	4	5	4	5	4	5	4	3
OPERATING PROFIT MARGIN	5	5	5	4	5	4	3	4	5
CURRENT RATIO	4	5	4	5	4	5	4	3	4
QUICK RATIO	5	5	5	5	4	5	4	5	3
ASSET TURNOVER	4	4	4	5	4	5	4	5	3
MANAGEMENT STRUCTURE	4	4	4	5	5	4	5	3	5
SUCCESSION PLANNING	4	3	4	5	4	3	3	2	4
STRATEGIC PLANNING	3	3	3	3	4	5	3	4	2
CORPORATE GOVERNANCE	4	4	4	5	5	5	3	4	5
OWNERSHIP STRUCTURE	3	5	4	4	5	4	5	4	3
DIVERSIFICATION OF INCOME	4	4	5	4	5	4	3	3	5
PAYMENT RECORDS	5	5	4	5	4	5	4	3	4
COMPANY AUDITORS	3	3	3	2	3	4	5	3	4
QUALITY AND TRANSPARENCY OF REPORTING	3	4	4	5	5	5	5	3	4
COMPETITIVENESS	4	5	5	5	4	5	3	4	5
POSITION IN THE INDUSTRY/MARKET	3	4	5	5	5	5	4	5	4
RISK OF INDUSTRY	3	3	3	4	3	4	2	3	4
GROUPS OF COUNTRY RISK	4	5	5	5	5	4	4	3	4

Table 2. Results of the Delphi method.

	VARIABLES	AVERAGE SCORE	ACCEPT/REJECT
1	debt-to-equity ratio	4.333333333	Accept
2	debt ratio to EBITDA	4.444444444	Accept
3	DSCR	4.444444444	Accept
4	interest coverage ratio	4.444444444	Accept
5	cash from operating activities ratio to total sales	4.555555556	Accept
6	ROE	4.222222222	Accept
7	operating profit margin	4.444444444	Accept
8	current ratio	4.222222222	Accept
9	quick ratio	4.555555556	Accept
10	asset turnover	4.222222222	Accept
11	management structure	4.333333333	Accept
12	succession planning	3.555555556	Reject
13	strategic planning	3.333333333	Reject
14	corporate governance	4.333333333	Accept
15	ownership structure	4.111111111	Accept
16	diversification of income	4.111111111	Accept
17	payment records	4.333333333	Accept
18	company auditors	3.333333333	Reject
19	quality and transparency of reporting	4.222222222	Accept
20	competitiveness	4.444444444	Accept
21	position in the industry/market	4.444444444	Accept
22	risk of industry	3.222222222	Reject
23	groups of country risk	4.333333333	Accept

Table 3. References of variables.

Factor	References
debt-to-equity ratio	[28,29]
debt ratio to EBITDA	[30,31]
DSCR	[32,33]
interest coverage ratio	[34,35]
cash from operating activities ratio to total sales	[36]
ROE	[37–39]
operating profit margin	[40,41]
current ratio	[42,43]
quick ratio	[41,44,45]
asset turnover	[46,47]
management structure	[48]
corporate governance	[49,50]
ownership structure	[50,51]
diversification of income	[52,53]
payment records	[54]
quality and transparency of reporting	[55,56]
competitiveness	[57–59]
company position	[60]
country risk	[61,62]

We used MATLAB (version 2015b, created by Cleve Moler, University of New Mexico, matrix laboratory, USA) and a fuzzy inference system to evaluate the variables.

4. Data Analysis

As shown in the previous section, the input variables (accepted variables according to Table 2) were debt-to-equity ratio, debt ratio to EBITDA (earnings before interest, tax, depreciation and amortization), DSCR (debt service coverage ratio), interest coverage ratio, cash from operating activities ratio to total sales, ROE (return on equity), operating profit margin, current ratio, quick ratio, asset turnover, management structure, corporate governance, ownership structure, diversification of income, payment records, quality and transparency of reporting, competitiveness, company position, and country risk. Table 3 provides an overview of these variables together with further references.

Table 4 shows the ranges of ratings for these variables, which were based on the opinions of experts from the Delphi method. These ranges are based on the broad experiences of the experts and provide valuable information to specify the FIS.

Table 4. Ranges of each variable and relationships to linguistic variables.

Variable	Range	
debt-to-equity ratio	$x > 150\%$	very poor
	$125\% \leq x \leq 150\%$	almost very poor
	$100\% \leq x \leq 125\%$	poor
	$75\% \leq x \leq 100\%$	average
	$50\% \leq x \leq 75\%$	good
	$x < 50\%$	very good

Table 4. *Cont.*

Variable	Range	
debt ratio to EBITDA	$x > 5$	very poor
	$4 \leq x \leq 5$	poor
	$3 \leq x \leq 4$	average
	$2 \leq x \leq 3$	good
	$x < 2$	very good
DSCR	$x < 1$	very poor
	$1 \leq x \leq 1.25$	poor
	$1.25 \leq x \leq 1.75$	average
	$1.75 \leq x \leq 2.5$	good
	$x > 2.5$	very good
interest coverage ratio	$x < 1$	very poor
	$1 \leq x \leq 2$	poor
	$2 \leq x \leq 4$	average
	$4 \leq x \leq 7$	good
	$x > 7$	very good
cash from operating activities ratio to total sales	$x < 5\%$	very poor
	$5\% \leq x \leq 12.5\%$	poor
	$12.5\% \leq x \leq 20\%$	average
	$20\% \leq x \leq 30\%$	good
	$x > 30\%$	very good
ROE	$x < 5\%$	very poor
	$5\% \leq x \leq 10\%$	poor
	$10\% \leq x \leq 15\%$	average
	$15\% \leq x \leq 20\%$	good
	$x > 20\%$	very good
operating profit margin	$x < 5\%$	very poor
	$5\% \leq x \leq 10\%$	poor
	$10\% \leq x \leq 17.5\%$	average
	$17.5\% \leq x \leq 25\%$	good
	$x > 25\%$	very good
current ratio	$x < 1$	very poor
	$1 \leq x \leq 1.25$	poor
	$1.25 \leq x \leq 1.75$	average
	$1.75 \leq x \leq 2.5$	good
	$x > 2.5$	very good

Table 4. *Cont.*

Variable	Range	
quick ratio	$x < 0.5$	very poor
	$0.5 \leq x \leq 0.75$	poor
	$0.75 \leq x \leq 1.25$	average
	$1.25 \leq x \leq 1.75$	good
	$x > 1.75$	very good
asset turnover	$x < 0.5$	very poor
	$0.5 \leq x \leq 1$	poor
	$1 \leq x \leq 1.5$	average
	$1.5 \leq x \leq 2$	good
	$x > 2$	very good
management structure	inadequate	
	below average	
	average	
	above average	
	adequate	
corporate governance	weakness	
	average	
	satisfied	
	very good	
	excellent	
ownership structure	weakness	
	average	
	satisfied	
	very good	
	excellent	
diversification of income	one specific income	
	limited	
	balanced	
	highly diversified income	
	very highly diversified income	
payment records	very poor	
	poor	
	average	
	good	
	very good	

Table 4. *Cont.*

Variable	Range
quality and transparency of reporting	very poor
	poor
	average
	good
	very good
competitiveness	enemy
	aggressive
	average
	suitable
	without threat
company position	starter
	small performer
	middle performer
	main performer
	market leader
country risk	highest risk
	almost high risk
	often risk
	middle risk
	low risk
	very low risk
	no risk

Table 5 shows how we created the membership function of each variable and IF-THEN rules. Then, we employed the IF-THEN rules to categorize agencies based on the input variables.

We utilized numerous IF-THEN rules to evaluate the input variables as shown in Table 5. These rules are based on input variables and their membership functions. We extracted the data of each company by considering the practical variables we obtained via the Delphi method. We then identified the highest percentage, average, and the lowest percentage of the triangular fuzzy membership function of each variable. As specified above (Equation (1)), a triangular membership function uses the parameters a, b, and m. The percentage values are denoted as alpha-cuts and are calculated according to [63]. An alpha-cut corresponds to the set of elements whose membership grades are greater than or equal to the specified value of alpha. Equation (3) shows how the alpha-cut is calculated:

$$[\mathrm{A}]^{\alpha} = [a - m(1-\alpha), a + b(1-\alpha)]. \quad (3)$$

We combined them based on the FIS and separated them into seven categories based on their levels of risk. This study helps managers make decisions and decreases the probability of a company defaulting.

Table 5. IF-THEN rules. For each of the seven evaluation categories, a respective rule is shown.

If	If	If	If	If	If	If	If	If	If	If	If	If	If	If	If	If	If	If	then
very poor	very poor	very poor	very poor	very poor	very poor	very poor	very poor	very poor	very poor	inadequate	weakness	weakness	one specific income	very poor	very poor	enemy	starter	highest risk	7
very poor	very poor	very poor	very poor	very poor	very poor	very poor	very poor	very poor	very poor	Inadequate	weakness	weakness	one specific income	very poor	very poor	enemy	starter	almost high risk	6
almost poor	poor	poor	poor	poor	poor	poor	poor	poor	poor	below average	average	average	limited	poor	poor	aggressive	small performer	often risk	5
poor	average	average	average	average	average	average	average	average	average	average	satisfied	satisfied	balanced	average	average	average	middle performer	middle risk	4
average	good	good	good	good	good	good	good	good	good	above average	very good	very good	highly diversified income	good	good	suitable	main performer	low risk	3
good	very good	very good	very good	very good	very good	very good	very good	very good	very good	adequate	excellent	excellent	very highly diversified income	very good	very good	without threat	market leader	very low risk	2
very good	very good	very good	very good	very good	very good	very good	very good	very good	very good	adequate	excellent	excellent	very highly diversified income	very good	very good	without threat	market leader	no risk	1

In Table 5, all variables which are extracted from the model and their data are transferred to fuzzy data. The change from crisp data to fuzzy data is based on Table 4. Based on the FIS logic and following an OECD (Organisation for Economic Co-operation and Development) rating concept based on seven categories or classes, the data is classified, that is, the rankings of customer companies are determined.

The membership function of each class is shown below in Figure 1. The figure presents an overview of the seven individual membership functions which are mathematically specified in Equations (4)–(10). Some researchers believe that the use of the Mamdani and Sugeno methods yields the same results [64,65].

$$\mu_{\widetilde{A_7}} = \begin{cases} \frac{x-16.67}{-2.97+16.67}, -16.67 \leq x \leq -2.97 \\ \frac{16.67-x}{16.67+2.97}, -2.97 \leq x \leq 16.67 \\ 0, \quad otherwise \end{cases} \tag{4}$$

$$\mu_{\widetilde{A_6}} = \begin{cases} \frac{x-0}{16.67-0}, 0 \leq x \leq 16.67 \\ \frac{33.33-x}{33.33-16.67}, 16.67 \leq x \leq 33.33 \\ 0, \quad otherwise \end{cases} \tag{5}$$

$$\mu_{\widetilde{A_5}} = \begin{cases} \frac{x-16.67}{33.33-16.67}, 16.67 \leq x \leq 33.33 \\ \frac{50-x}{50-33.33}, 33.33 \leq x \leq 50 \\ 0, \; otherwise \end{cases} \tag{6}$$

$$\mu_{\widetilde{A_4}} = \begin{cases} \frac{x-33.33}{50-33.33}, 33.33 \leq x \leq 50 \\ \frac{66.67-x}{66.67-50}, 50 \leq x \leq 66.67 \\ 0, \; otherwise \end{cases} \tag{7}$$

$$\mu_{\widetilde{A_3}} = \begin{cases} \frac{x-50}{66.67-50}, 50 \leq x \leq 66.67 \\ \frac{83.33-x}{83.33-66.67}, 66.67 \leq x \leq 83.33 \\ 0, \; otherwise \end{cases} \tag{8}$$

$$\mu_{\widetilde{A_2}} = \begin{cases} \frac{x-66.67}{83.33-66.67}, 66.67 \leq x \leq 83.33 \\ \frac{100-x}{100-83.33}, 83.33 \leq x \leq 100 \\ 0, \; otherwise \end{cases} \tag{9}$$

$$\mu_{\widetilde{A_1}} = \begin{cases} \frac{x-83.33}{100-83.33}, 83.33 \leq x \leq 100 \\ \frac{116.7-x}{116.7-100}, 100 \leq x \leq 116.7 \\ 0, \; otherwise \end{cases} \tag{10}$$

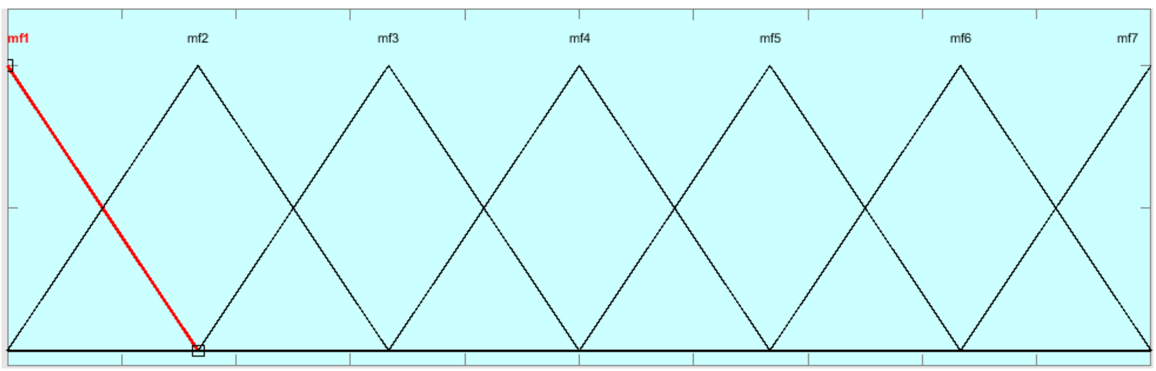

Figure 1. Membership function of output variable.

With regard to the Export Guarantee Fund of Iran, each company was placed into one of the seven categories. Category 7 attributes to a company the highest risk and probability of default, whereas a category 1 placement represents the lowest risk and the lowest probability of default. Managers can use these membership functions to determine whether they will do business with a company.

5. Conclusions

In this uncertain world, most managers attempt to make decisions with the help of managerial tools. Based on these tools, managers can make accurate decisions in areas such as economics, politics, and finance. An important goal is to increase the economic growth rate of countries through exporting. Many nations have established ECAs to support exporters and avoid trade risks. However, because the situation of each country is unique, each agency must create a customized model to help agents analyze credit ratings in their specific countries. In this study, we extracted the key variables for credit rating using the Delphi method. Among the 23 possible variables extracted using Moody's method, only 19 were classified as suitable. We used a fuzzy inference system to determine the credit rating membership function. We then separated the output membership functions into seven categories. Based on these variables and the range of each variable, we used IF-THEN rules to measure the output membership functions to show how these variables affect credit ratings and how credit is allocated to each category based on the membership function.

The proposed method offers the following advantages for determining the credit ratings of companies. First, the proposed FIS method helps managers of the EGFI to rate companies in an uncertain environment. It allows them to determine the risk and the probability of default of a company. Second, the experts of EGFI evaluated the credit rating input variables using the Delphi method. They selected 19 suitable input variables to enter into the FIS method. Third, the FIS method considers not only quantitative ratings but also qualitative values and linguistic terms in an uncertain environment. This method is practical for rating the creditworthiness of companies in the real world.

As mentioned above, the described FIS was customized for the Export Guarantee Fund of Iran (EGFI) for evaluating the credit ratings of buyer companies to determine whether to grant credit to exporters. Due to the general economic situation of Iran and budget limitations, it is crucial to support respective decisions by a well-designed software tool. It will be part of future research to further evaluate the use of the model and its results in the given application scenario.

Apart from the specific FIS developed and applied during our study, the paper shows in general how the considered methodologies can be used in practice. This should help applying the techniques in other settings as well.

For future research, the proposed procedure and FIS model may be applied to other credit rating systems in other countries. In particular, related research may provide further insights regarding a broader empirical validity of obtained information (such as ranges in Table 4 or IF-THEN rules in Table 5).

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