

Bankruptcy Prediction Model with Risk Factors using Fuzzy Logic Approach

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HIGHLIGHTS

- A bankruptcy prediction model was developed using fuzzy logic approach.
- Qualitative risk factors of 250 respondents from banks and financial firms were tested.
- A comprehensive analysis is conducted using the Fuzzy Inference System (FIS) editor in MATLAB.
- An accurate bankruptcy prediction model was developed to determine the tendency of bankruptcy.

ABSTRACT

Forecasting bankruptcy remains crucial, especially during this pandemic. Managers, financial institutions, and government agencies rely on the information regarding an impending bankruptcy threat to make decisions. This paper developed a straightforward bankruptcy prediction model using the fuzzy logic approach for individuals and companies to evaluate their performance and analyse the tendency of getting bankrupt. A sample of 250 respondents from banks and financial firms were tested using the qualitative risk factors, namely, industrial risk, management risk, financial flexibility, credibility, competitiveness, and operational risk. This study provides a comprehensive analysis using the Fuzzy Inference System (FIS) editor in the MATLAB software, where the model's accuracy is compared to the actual results. The results show an accuracy rate of 99.20%, indicating that this approach can determine the likelihood of bankruptcy. The fuzzy logic approach can improve prediction accuracy while also guiding decision-makers in detecting and preventing possible financial crises in their early phases.

Keywords: bankruptcy prediction, fuzzy logic, risk factors, Fuzzy Inference System

INTRODUCTION

Bankruptcy happened when a person or a company is incapable of paying its debts. The recent COVID-19 pandemic outbreak showed an increase in individual and company bankruptcy. Despite the rollout of the vaccination programme and optimistic economic growth numbers, worldwide bankruptcies are expected to rise by 26% in 2021 (Gerryn, 2021). For the first quarter of 2021, there are 1864 bankruptcies recorded in Malaysia (Malaysian Department of Insolvency, 2021). However, this figure could change due to the Movement Control Order (MCO) implementation since May 12, 2021, and after the 6-month loan repayment moratorium end in early 2022. Brown and Rocha (2020) found that the present pandemic has



harmed economic activity, which has impacted the debt market, resulting in a worldwide financial catastrophe.

Bankruptcy prediction is an essential tool for managers, financial institutions, and government agencies. Managers and financial institutions use this tool to decide on lending out new credit proposals by assessing the potential risks of becoming bad debts. At the same time, government agencies use the output of prediction tools as an indicator of a country's economic development and strength. Statistical models and artificial intelligence models are two major types of models use to forecast bankruptcy. In the 1960s, Beaver (1966) and Altman (1968) initiated studies on predicting bankruptcy. Since the works of Beaver and Altman, various statistical techniques have been used in numerous research studies (Alaka et al., 2018; Balcaen & Ooghe, 2006; Giannopoulos & Sigbjørnsen, 2019; Jackson & Wood, 2013). According to Balcaen and Ooghe (2006), multivariate discriminant analysis and logistic regression models are two widely used statistical methods. Although statistical methods are widely employed in bankruptcy prediction, they have numerous flaws in statistical assumptions such as linearity, normality, and independence among variables that have been documented in multiple publications (Jayasekera, 2018; Tian & Yu, 2017). As a result, intelligent bankruptcy prediction techniques, including neural networks, genetic algorithms, vector support machines, and fuzzy logic, have gained prominence (Dong et al., 2018; García et al., 2019; Hosaka, 2019). The research domain of bankruptcy prediction continues to evolve with different predictive models using various methods (J et al., 2020; Jabeur & Serret, 2021; Jaki & Cwięk, 2020). Chen et al. (2009) proposed a neuro-fuzzy bankruptcy prediction model. This model showed a more substantial detection power, a higher accuracy rate, and a lower misclassification cost, indicating that it might be highly effective in delivering warnings of imminent insolvency. Consistent with this finding, Jabeur and Serret (2021) showed that fuzzy convolutional neural networks outperformed conventional approaches. All these studies showed the competence of the fuzzy logic applied in the bankruptcy prediction model.

Despite the earlier bankruptcy modelling efforts, there is still a lack of bankruptcy dynamics research using a straightforward model. Therefore, this paper proposed a straightforward bankruptcy prediction model using the fuzzy logic approach. This model calculated the respondents' risk of bankruptcy by identifying and analysing risk factors. The remainder of this paper is organised as follows. First, pre-processing the data and apply fuzzy logic in the prediction model. Next, the results of this study are analysed and presented. Finally, a summary of the results is discussed.

METHODOLOGY

The data used in this study was collected by experts and submitted to the University of California, Irvine (UCI) repository in 2014 (Martin et al., 2014). The information includes datasets on qualitative risk factors such as industrial risk, management risk, financial flexibility, credibility, competitiveness, and operational risk affecting the risk of bankruptcy, involving 250 respondents from banks and financial firms.

A static nonlinear mapping represents the inputs and outputs of a fuzzy system. Figure 1 depicts a basic configuration of Fuzzy Inference System.



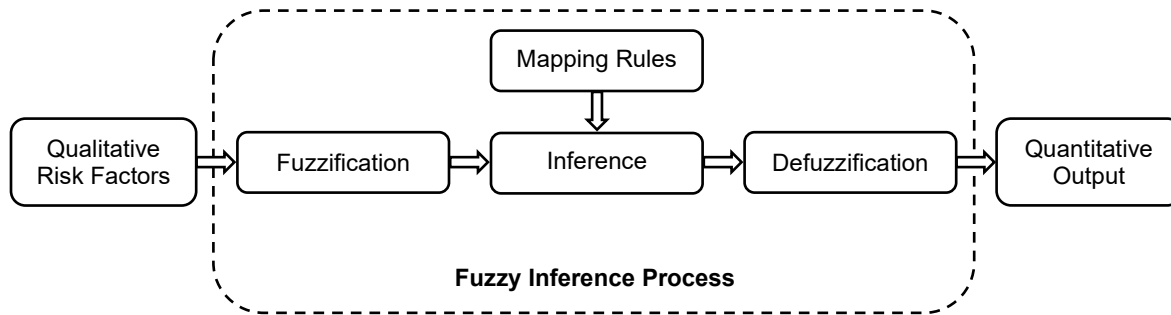


Figure 1: Basic configuration of Fuzzy Inference System

Fuzzification

MATLAB utilised its technique to categorise the datasets into a linguistic variable to measure the membership function, using the Fuzzy Inference System (FIS) tools. Fuzzy logic, often known as approximation reasoning, is based on fuzzy rules formulated in natural language via linguistic variables. In math-based calculation, variables generally take numerical values, while in fuzzy logic, variables take linguistic variables (Azimjonov, 2016). The qualitative risk factors in this study were split into three attributes: positive, average, and negative, which served as inputs to the fuzzy logic approach, with bankrupt and non-bankrupt as outputs. The trapezoidal and triangular membership functions were used to define the data's input and output (Kreinovich et al., 2020). The data was graded depending on the membership meaning.

Fuzzy Inference System and Fuzzy Rules

“IF-THEN” rules were applied to the data. The inference statement comprises a knowledge base and rules necessary for the output to be generated. Setting up the rules was programmed using the rule editor function. There were six inputs with three linguistic expressions and one output with two linguistic expressions used in this study. The fuzzy logic-based evaluation model used the data gathered from this group. Mamdani modelling was utilised for fuzzy inference and fuzzy decision-making to derive the output membership functions for each rule (Mamdani & Assilian, 1975). Table 1 shows a sample of 10 rules from a total of 25 rules generated. IR, MR, FF, CR, CO, and OR refer to industrial risk, management risk, financial flexibility, credibility, competitiveness, and operational risk, respectively, while P, A, N, B, and NB refer to positive, average, negative, bankrupt and non-bankrupt respectively.

Table 1: A sample of IF-THEN rules

Rule	IR	MR	FF	CR	CO	OR	Class Distribution
1	N	N	N	N	N	N	B
2	A	A	A	A	A	A	NB
3	P	P	P	P	P	P	NB
4	P	P	A	A	A	P	NB
5	N	N	A	A	A	N	NB
6	N	N	P	P	P	N	NB
7	A	N	N	N	N	A	B
8	P	N	N	N	N	P	B
9	A	P	N	A	N	N	B
10	N	N	A	A	P	N	NB



Figure 2 shows the setup of IF-THEN rules from the Rule Editor in MATLAB.

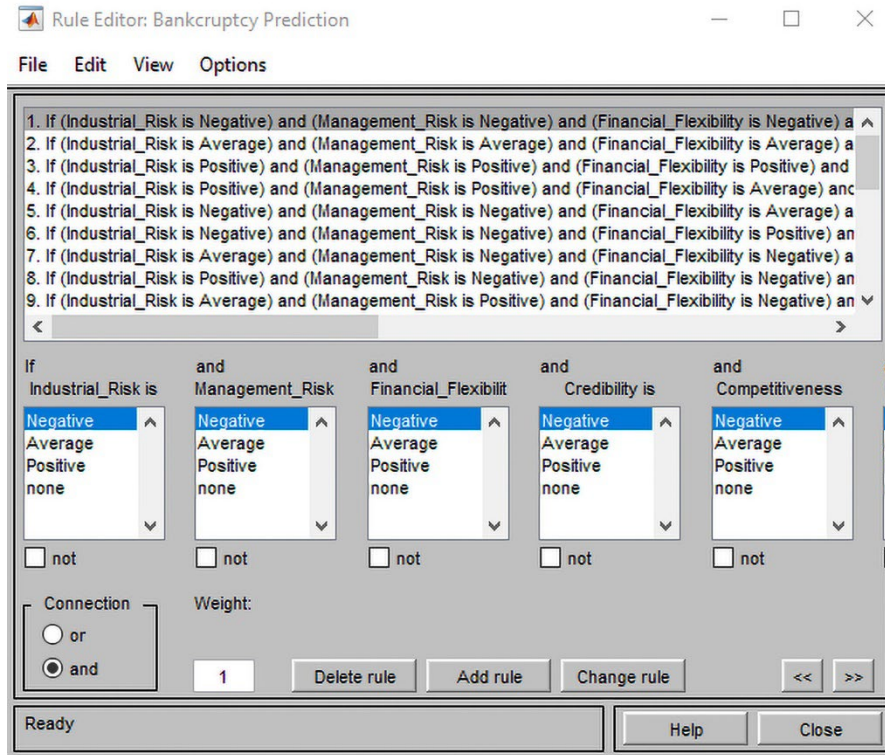


Figure 2: Rule Editor

Defuzzification

Defuzzification is a process of transforming the fuzzy output into a crisp output. The centroid defuzzification method was used to obtain the bankruptcy risk rate since it is the most common method that several researchers used. The centroid method is also known as the centre of parameters that were calculated based on Eq. (1).

$$Z = \frac{\int_a^b \mu_A(x) x dx}{\int_a^b \mu_A(x) dx} \quad (1)$$

Where Z is the crisp output, μ_A is the aggregated membership function, while x is the output variable. Figure 3 illustrates the membership function for output that is the class distribution.



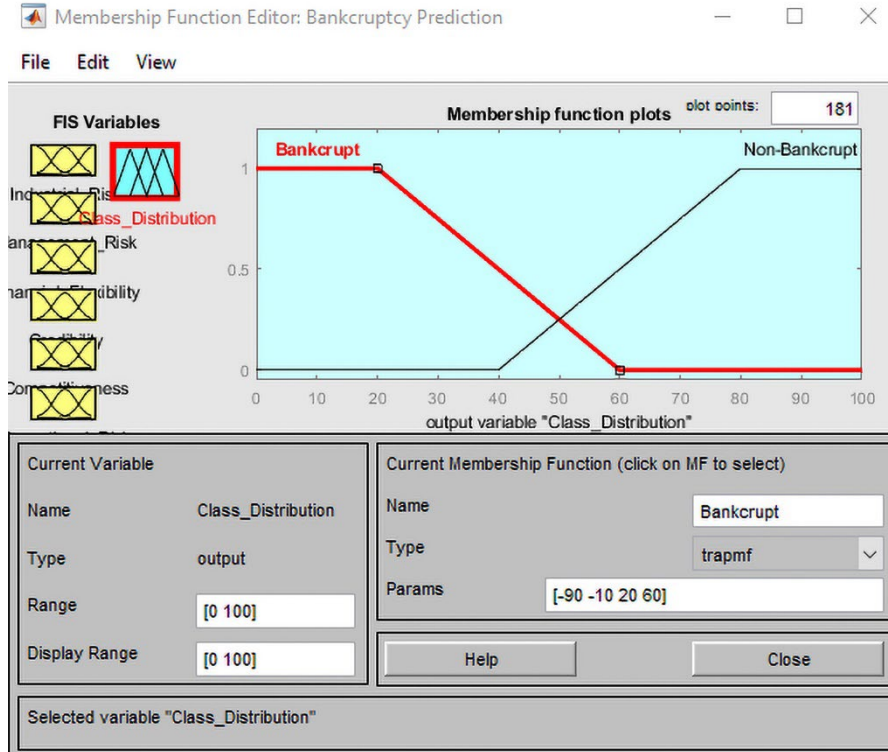


Figure 3: Membership Function for Class Distribution

RESULTS AND DISCUSSION

The rules for this study were retrospectively extracted from 250 respondents, where it produced 25 rules. The rules were developed by merging the input and output variables and investigating their relationship. Defuzzification is the mathematical process of associating a value from a non-fuzzy space with a fuzzy value provided by a fuzzy model through reasoning. The defuzzification value is obtained through the Rule Viewer function in the MATLAB software. Figure 4 shows the performance analysis where the yellow-coloured graph is the inputs, and the blue coloured graph is the output. The value above the blue coloured graph is identified as the fuzzy number or defuzzification value. Figure 5 shows the 3-D surface viewer of the performance analysis.



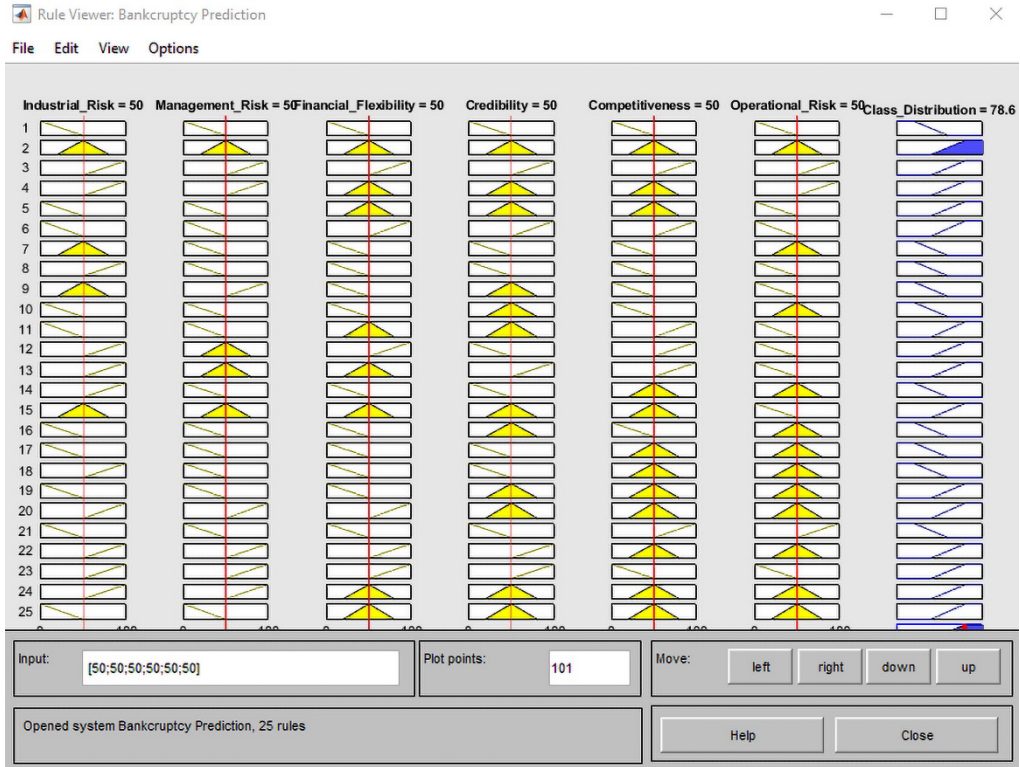


Figure 4: Performance analysis

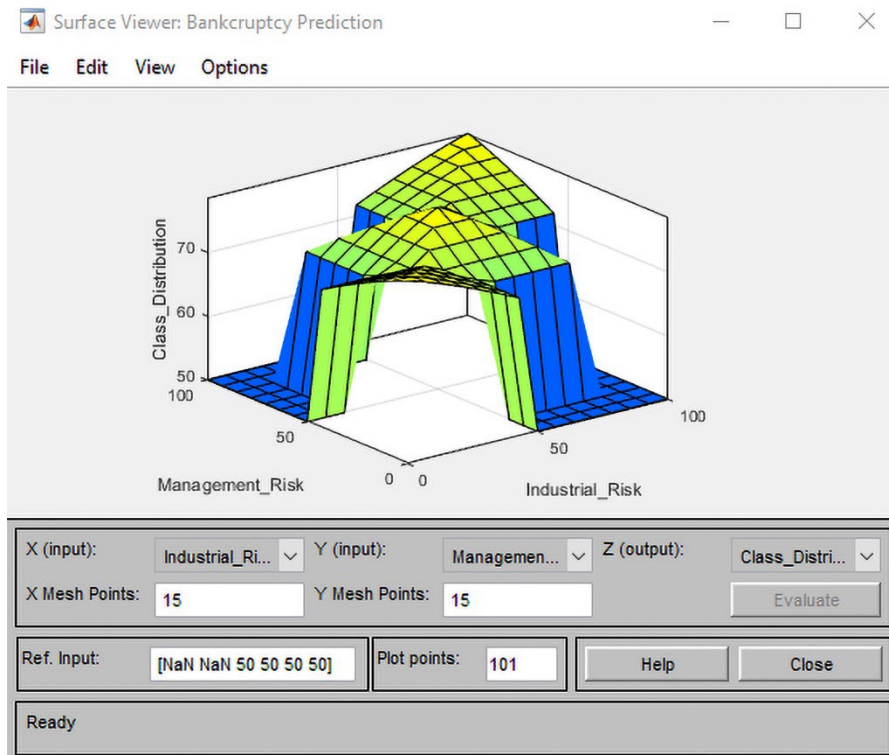


Figure 5: 3-D Surface Viewer



Table 2 shows a portion of the outputs from a total of 250 outputs obtained from MATLAB. The respondents' data accuracy was compared with the actual results.

Table 2: A portion of the outputs from the Fuzzy Inference System and actual results

No	IR	MR	FF	CR	CO	OR	Defuzzification value	Class Distribution	Actual Result
1	P	P	A	A	A	P	76.1	NB	NB
2	N	N	A	A	A	N	75.1	NB	NB
3	A	A	A	A	A	A	78.1	NB	NB
4	P	P	P	P	P	P	76.1	NB	NB
5	N	N	P	P	P	N	74.7	NB	NB
6	A	A	P	P	P	A	72.9	NB	NB
7	P	P	A	P	P	P	70.5	NB	NB
8	P	P	P	A	A	P	71.3	NB	NB
9	P	P	A	P	A	P	70.8	NB	NB
10	P	P	A	A	P	P	73.7	NB	NB
11	P	P	P	P	A	P	70.8	NB	NB
12	P	P	P	A	P	P	72.5	NB	NB
13	N	N	A	P	P	N	70.8	NB	NB
14	N	N	P	A	A	N	70.8	NB	NB
15	N	N	A	P	A	N	71.7	NB	NB
16	N	N	A	P	A	N	71.7	NB	NB
17	N	N	A	A	P	N	73.9	NB	NB
18	N	N	P	P	A	N	70.8	NB	NB
19	N	N	P	A	P	N	71.3	NB	NB
20	A	A	A	P	P	A	71.1	NB	NB

This study produced two types of results, which are bankrupt and non-bankrupt. A range is specified to categorise the fuzzy number to identify the output to classify whether the respondents are bankrupt or non-bankrupt. For the output to obtain non-bankrupt, the fuzzy number must be more than or equal to 50 (Defuzzification Value ≥ 50), and for the output to obtain bankrupt, the fuzzy number must be less than 50 (Defuzzification Value < 50). The results showed that almost all results obtained from the MATLAB software are matched to the actual results. However, two outputs from the respondents' numbers 86 and 216 differ from the actual results. This study showed that 248 outputs out of 250 are matched with the actual results. The following calculation is used to calculate the accuracy of the bankruptcy prediction proposed by this study.

$$\begin{aligned}
 \text{Accuracy of bankruptcy prediction} &= \frac{\text{Matched Results}}{\text{Total Actual Results}} \times 100\% \\
 &= \frac{248}{250} \times 100\% \\
 &= 99.20\%
 \end{aligned} \tag{2}$$



CONCLUSION AND RECOMMENDATION

The fuzzy logic approach is used to analyse the bankruptcy performance of the proposed model. Interestingly, the accuracy rate obtained from this study is 99.20%. The excellent accuracy rate indicates that the straightforward bankruptcy prediction model using the fuzzy logic approach can develop an accurate bankruptcy prediction model. The findings revealed that industrial risk, management risk, financial flexibility, credibility, competitiveness, and operational risk play essential roles in predicting an individual's or a company's risk of bankruptcy. This study provides valuable insight into developing a bankruptcy prediction model that could efficiently determine bankruptcy. As a result, a more straightforward model for predicting bankruptcy has been developed, which is vital for individuals and companies to forecast bankruptcy more efficiently, thus preventing the country's economic position from worsening. Feature selection in the input level should be considered for future works to reduce the computational complexity and provide a higher performance of the bankruptcy prediction model.

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CONFLICT OF INTERESTS DECLARATION

The authors declare no conflict of interests regarding the publication of this article.

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