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Big five personality with fuzzy approach to feasibility assessment and loan determination for peer-to-peer lending

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ABSTRACT

Bad credit is an uncollectible receivable because the debtor has difficulty repaying. In May 2023, the number of loans will increase by 3.36%. This is due to the inaccuracy of creditors in assessing prospective debtors. Several methods of valuation of prospective debtors have been widely used, but the use of the test big five personality (TBFP) method for the assessment of prospective debtors has not been found. This study will use TBFP as an input variable that will be calculated using fuzzy-Mamdani. The output of the system is in the form of a recommended percentage (%) of the loan amount. This research needs to be done to provide an assessment of prospective debtors to be more objective so that bad credit problems can be reduced. The results of this study are taken into consideration to be used as input in assessing prospective debtors that are more appropriate so that it has an impact on increasing income. For the community can increase business activities. For the government to help people's economic activities. Our research still needs to be developed by adding variables such as the financial condition of prospective debtors, psychological values, and loan history. Apart from that, it is necessary to carry out an in-depth study regarding recommendations for loan amounts for bad credit

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1. INTRODUCTION

Bad credit is bad debt or credit that has substandard criteria, because it has strain repaying due to certain factors. Bad loans are part of non-performing loans [1]. Bad loans can occur if the Bank has difficulty requesting installments from the debtor due to the debtor's financial condition. In May 2023, the financial services authority recorded that the number of bad loans in P2P lending or online loans increased [2]. The increase in bad loans based on the default rate (TWP) of 90 which increased to 3.36% as of May 2023. The aggregate credit risk level increased by 28.11% or IDR. 51.46 trillion compared to the April 2023 period [3].

Corrupt credit problems are caused by several internal and external factors. Internal factors such as expansive credit policies, faults in the execution of procedures, credit scoring, errors in assessment and granting of credit loan amounts that are less appropriate, and frail bad credit information systems. While external factors are the failure of the debtor's efforts to fulfill obligations that have been mutually agreed between the creditor and the debtor due to intentional or out-of-control factors [4]. In February 2023, as many as 25 debtors in official online loan companies in Indonesia experienced bad loans resulting in company losses of IDR.

975,000,000. If no improvement is made, non-performing loans will continue to increase which can result in losses for various parties due to non-receipt of funds that have been distributed. The lender will lose income from interest resulting in a decrease in total income [5].

Bank Indonesia (BI) classifies five credit qualities, namely (i) current (pas) means that the credit disbursed does not cause problems, (ii) special mention means that the credit given has begun to have problems, so it needs attention, (iii) substandard means credit whose payments have begun to be not smooth, but the debtor is still able to pay, (iv) doubtful, namely the debtor's ability to pay increasingly uncertain, and (v) loss if the debtor is no longer able to pay the loan, so it needs to be saved [6]. Providing credit that runs smoothly will develop and increase a country's economic activities. Loans provided in the form of credit come from public funds, so there is a high risk of not returning credit on time or non-performing loan (NPL). The level of creditor health can be measured from the level of non-performing loan ratios which can result in disruption of creditor liquidity [7].

The problem of bad credit is caused by several internal and external factors. Internal factors such as expansive credit policies, errors in implementing procedures, errors in assessment and granting of inappropriate credit loan amounts, and weak bad credit information systems. Meanwhile, external factors are the failure of the debtor's efforts to fulfil obligations that have been mutually agreed between the creditor and the debtor due to intentional factors or factors beyond the control [8]. In February 2023, as many as 25 debtors at official online loan companies in Indonesia experienced bad credit which resulted in company losses of IDR. 975,000,000. If improvements are not made, non-performing loans will continue to increase which could result in losses for various parties due to non-receipt of funds that have been distributed. Credit providers will lose income from interest which results in a decrease in total income [9].

Loan application activities in Indonesia are generally carried out by filling in personal data such as Personal Identity, family data, income data into the application. After that, the system will check with Bank Indonesia regarding the track record of the prospective debtor. If no problems are found in the lending process, then the prospective debtor will be approved. Within 2 hours, the funds will be released to the prospective debtor by the creditor. The convenience offered provides opportunities for potential debtors to take advantage of this access by cheating because the system for personal detection of potential debtors does not yet exist in the system. Therefore, it is possible to develop a system to provide input to creditors regarding whether they are approved or not based on the characteristics of the prospective debtor.

Several efforts to overcome bad credit in Indonesia have been carried out using various methods. One common method is: (i) giving administrative fines, (ii) giving reduced fines, and (iii) paying interest in instalments. However, this method is still not optimal, it needs to be combined with other approaches [10]. Another approach uses the principle of "Pang Pade Payu". The application of this method is not effective enough even though it uses a family approach, it is necessary to assess customers before making a loan application [11]. Implementation of rescheduling, reconditioning and restructuring approaches to reduce bad credit. Rescheduling is a legal effort to make changes to several terms of a credit agreement relating to the repayment schedule or changes to the number of instalments. Reconditioning is a change to part or all of the terms of the agreement which is not limited to changes to the instalment schedule or credit period. Restructuring is an improvement effort carried out by the Bank in credit activities for debtors, such as: (i) reducing credit interest rates; (ii) extension of the credit term; (iii) reduction in credit interest arrears; (iv) reduction of principal arrears on credit; (v) additional credit facilities; and (vi) conversion of credit into temporary capital participation [12], [13]. Assessment of prospective debtors to support credit provision using the 5C principles (character, capacity, capital, collateral, and condition) has been applied to several financial companies, but the results are still less than optimal due to limited implementation [14], [15].

Assessment of the character of prospective debtors using the test big five personality (TBFP) method such as (i) openness to experience, (ii) conscientiousness, (iii) extraversion, (iv) agreeableness, and (v) neuroticism has not been found. Several studies report that TBFP is able to help support decision making such as household financial management. The results show that there is a statistically significant influence between personality and financial characteristics in the management of various types of debt and assets [11]. In addition, TBFP can be applied to look at dispositional influences, and adult financial satisfaction. This research found that personality is one of the strongest predictors of life satisfaction [16]. The influence of TBFP was found to mean that this theory can be used to research personality in financial management [17]. In addition, the application of TBFP can be used to test the impact of financial literacy on investment decisions [18]. Financial institutions are recommended to provide counselling services for potential investors using consumer profiling techniques [17]. This research will apply TBFP to assess potential debtors to help provide credit for online loans. Prospective debtors will be given a questionnaire using the TBFP principle. The results of filling in the questionnaire will be used as input variables for fuzzy logic as the method we propose.

Fuzzy logic is a branch of mathematics and computer science that has a function to provide modeling of problem solving as done by humans with the help of computer technology [19]. Fuzzy logic can be used to create a basis for rules so as to draw appropriate conclusions [20]. Fuzzy logic has a function to provide problem-solving modeling as humans do with the help of computer technology. The use of fuzzy logic allows a problem statement to be solved easily with an accurate solution. Vague logic also has the purpose of solving problem formulations that contain uncertainty [19]. Research on the application of fuzzy logic in the economic field is proven to help creditors in determining the amount of loans that are in accordance with the conditions of prospective debtors. The study conducted [21] used a blend of fuzzy and neuro-symbolic methods for evaluating the creditworthiness of individuals applying for bank loans. In addition, fuzzy logic is able to classify loan risk [22]. Fuzzy-based software systems applied to banking companies are able to support loan decision making [23]. The application of the adaptive neuro fuzzy inference system (FIS) can help credit in predicting the amount of debtor loans [24].

Looking at several studies on the successful application of fuzzy logic in determining loans, the purpose of the study will be to apply fuzzy logic using TBFP principles to assist creditors in assessing the creditworthiness of prospective debtors. This research needs to be done to provide an assessment of prospective borrowers so that creditors are more objective in making decisions so that bad credit problems can be reduced. If this is done, it will have a good impact on some parties. For agencies or creditors, it can increase revenue, for the community it can increase business activities and increase the number of loans. For the government to help people’s economic activities.

2. METHOD

2.1. Proposed system

The current system is that prospective debtors must complete the required documents such as an id card for being >18 years old, having an income and a bank account. If the requirements have been met, the debtor must fill out the BFP questionnaire. The results of filling out the debtor’s questionnaire are used to calculate the loan amount. Calculations using logic using fuzzy logic with Mamdani’s FIS. Fuzzy logic has the function to provide modeling of problem solving as done by humans with the help of computer technology [19]. The advantages of fuzzy logic are being able to map the input space into an output space. The fuzzy logic computation consists of three steps: fuzzification of inputs, fuzzy inference associated with the rule base and defuzzification [25]. Input variables use the five principles of TBFP namely openness, conscientiousness, extraversion, agreeableness, and neuroticism. The input value will be calculated using fuzzy inference using the IF-then function. The system output results in the form of a recommendation for the percentage (%) of the loan are given to the Credit Analyst for verification. Figure 1 shows the steps of fuzzy logic is proposed system.

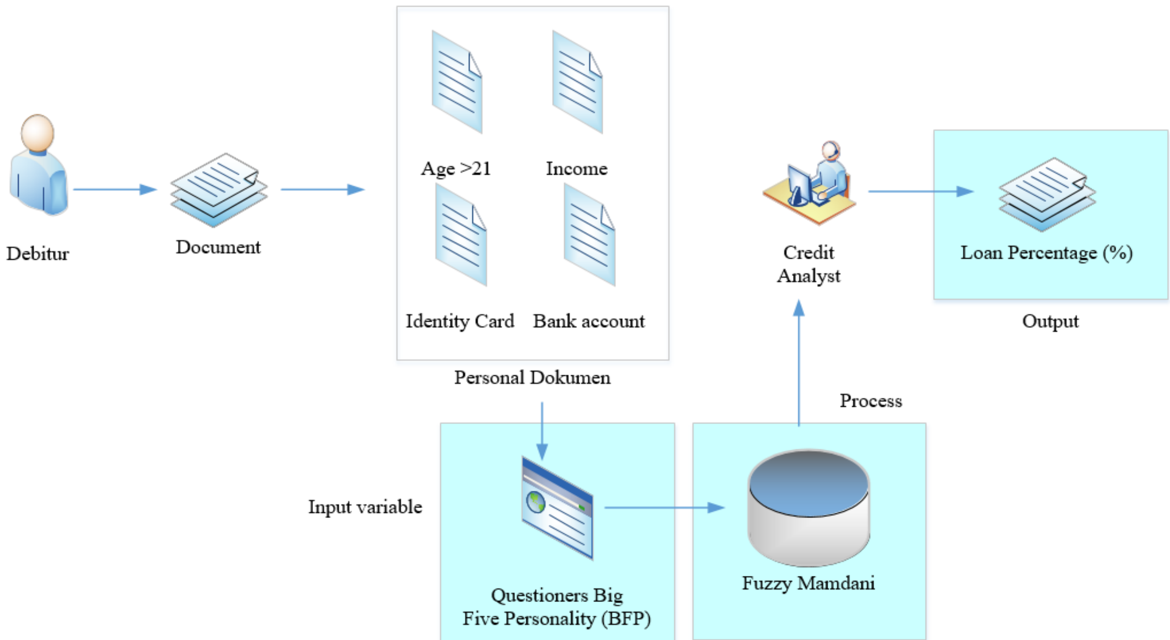


Figure 1. Proposed system using TBFP with fuzzy-Mamdani

2.2. Questioner test big five personality

The questionnaire was created using five input variables from TBFP namely openness, conscientiousness, extraversion, agreeableness, and neuroticism. Each variable has five questions. Each question must be filled in by the prospective debtor. Table 1 show questions and scores TBFP.

Table 1. Questioner TBFP

No	Question	Choices
1	Openness (O)	
	Do you like to try new things? (O1)	(100) Very Like (80) Like (60) Simply (40) Less (20) No
	Are you comfortable with a change? (O2)	(100) Very Like (80) Like (60) Simply (40) Less (20) No
	Do you feel like trying something you've never tried before? (O3)	(100) Very Like (80) Like (60) Simply (40) Less (20) No
	Do you find it difficult to strike up a conversation with someone you just met? (O4)	(100) Very Like (80) Like (60) Simply (40) Less (20) No
	Do you feel open to learning about cultures or traditions that are different from those you know? (O5)	(100) Very Like (80) Like (60) Simply (40) Less (20) No
2	Conscientiousness (C)	
	Do you feel compelled to do a perfect job? (C1)	(100) Very Like (80) Like (60) Simply (40) Less (20) No
	Are you used to planning before starting a project? (C2)	(100) Very Like (80) Like (60) Simply (40) Less (20) No
	Do you feel dissatisfied with yourself if you don't do a good job? (C3)	(100) Very Like (80) Like (60) Simply (40) Less (20) No
	Do you feel compelled to keep learning and improving yourself? (C4)	(100) Very Like (80) Like (60) Simply (40) Less (20) No
	Do you find it difficult to cooperate with people who are not very diligent? (C5)	(100) Very Like (80) Like (60) Simply (40) Less (20) No
3	Extraversioon (E)	
	Do you feel good about being in a crowd? (E1)	(20) Very Like (40) Like (60) Simply (80) Less (100) No
	Do you tend to talk a lot? (E2)	(20) Very Like (40) Like (60) Simply (80) Less (100) No
	Do you tend to be the center of attention among your friends? (E3)	(20) Very Like (40) Like (60) Simply (80) Less (100) No
	Do you feel good when given the opportunity to speak in public? (E4)	(20) Very Like (40) Like (60) Simply (80) Less (100) No
	Do you feel happy when invited to social events? (E5)	(20) Very Like (40) Like (60) Simply (80) Less (100) No
4	Agreeableness (A)	
	Do you tend to adjust to the needs of others? (A1)	(100) Very Like (80) Like (60) Simply (40) Less (20) No
	Do you feel good when you can help others? (A2)	(100) Very Like (80) Like (60) Simply (40) Less (20) No
	Do you tend to prioritize your personal interests over the interests of others? (A3)	(100) Very Like (80) Like (60) Simply (40) Less (20) No
	Do you tend to avoid confrontation with others? (A4)	(100) Very Like (80) Like (60) Simply (40) Less (20) No
	Do you tend to satisfy other people's desires even if they make you uncomfortable? (A5)	(100) Very Like (80) Like (60) Simply (40) Less (20) No
5	Neuroticism (N)	
	Do you often feel anxious? (N1)	(20) Very Like (40) Like (60) Simply (80) Less (100) No
	Don't you feel anxious when facing new situations? (N2)	(20) Very Like (40) Like (60) Simply (80) Less (100) No
	Do you often feel sad all of a sudden? (N3)	(20) Very Like (40) Like (60) Simply (80) Less (100) No
	Do you tend to experience rapid mood swings? (N4)	(20) Very Like (40) Like (60) Simply (80) Less (100) No
	Do you tend to think about things that could go wrong? (N5)	(20) Very Like (40) Like (60) Simply (80) Less (100) No

2.3. Input variables

The variable used is the TBFP given and filled in by prospective debtors. This test is used to assess the personality of prospective debtors. The TBFP personality theory consists of 5 key dimensions namely openness for experience, conscientiousness, extraversion, agreeableness, and neuroticism [16]. The input and output variables are shown in Figure 2.

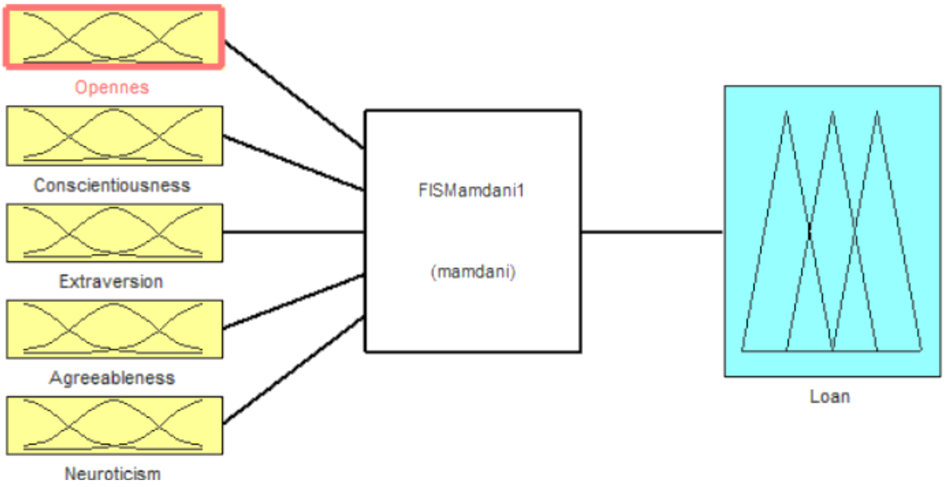


Figure 2. Input and output variables in the proposed system

2.3.1. Openness (O)

People can be grouped based on their interest in new things and their inclination to identify and acquire innovative elements. Those with a high level in this dimension tend to be more creative, imaginative, intellectual, curious, and open-minded. Conversely, individuals with a lower level in this dimension may lean towards conservatism and find contentment in existing things, often becoming apprehensive when faced with new tasks. The openness variables are categorized into three sets: "poor," "medium," and "high," as detailed in Table 2, with corresponding membership functions in Figure 3.

Table 2. Fuzzyfication of the input variable "Openness"

Input variable	Crisp set	Fuzzy set
Openness (Number)	0-50	Poor
	25-75	Medium
	50-100	High

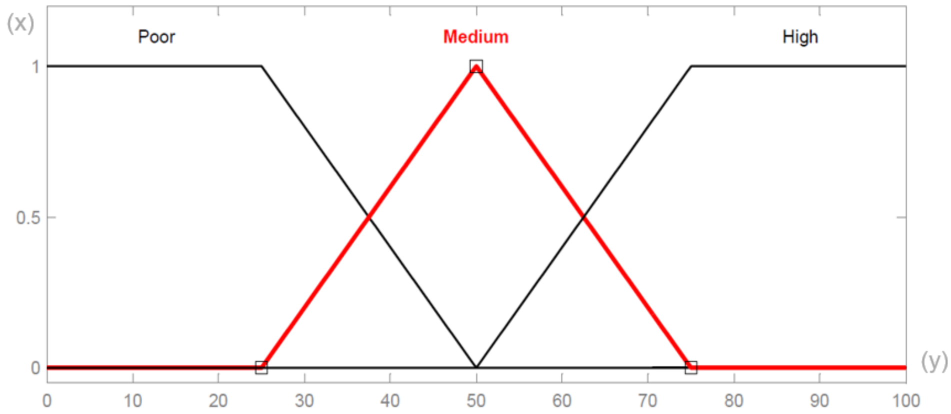


Figure 3. Membership functions for "openness"

$$\mu Poor[x] = \begin{cases} 1; & x \leq 25 \\ \frac{50-x}{50-25} & 25 \leq x \leq 50 \\ 0; & x \geq 50 \end{cases} \tag{1}$$

$$\mu Medium[x] = \begin{cases} 0; & 25 \geq x \geq 75 \\ \frac{x-25}{50-25} & 25 \leq x \leq 50 \\ \frac{75-x}{75-50} & 50 \leq x \leq 75 \end{cases} \quad (2)$$

$$\mu High[x] = \begin{cases} 0; & x \leq 50 \\ \frac{x-50}{65-50} & 50 \leq x \leq 75 \\ 1; & x \geq 75 \end{cases} \quad (3)$$

2.3.2. Conscientiousness (C)

Individuals exhibiting conscientiousness tend to approach actions and decisions with care and consideration. They often possess high self-discipline and are deemed trustworthy. Positive traits associated with conscientious individuals include consistency, accountability, hard work, and a focus on achievement. On the flip side, lower conscientiousness may manifest as irresponsibility, hastiness, disorganization, and reduced reliability in completing tasks. The conscientiousness variable is categorized into three sets: “poor,” “medium,” and “high,” as outlined in Table 3, with corresponding membership functions illustrated in Figure 4.

Table 3. Fuzzyfication of the input variable “conscientiousness”

Input variable	Crisp set	Fuzzy set
Conscientiousness (Number)	0-50	Poor
	25-75	Medium
	50-100	High

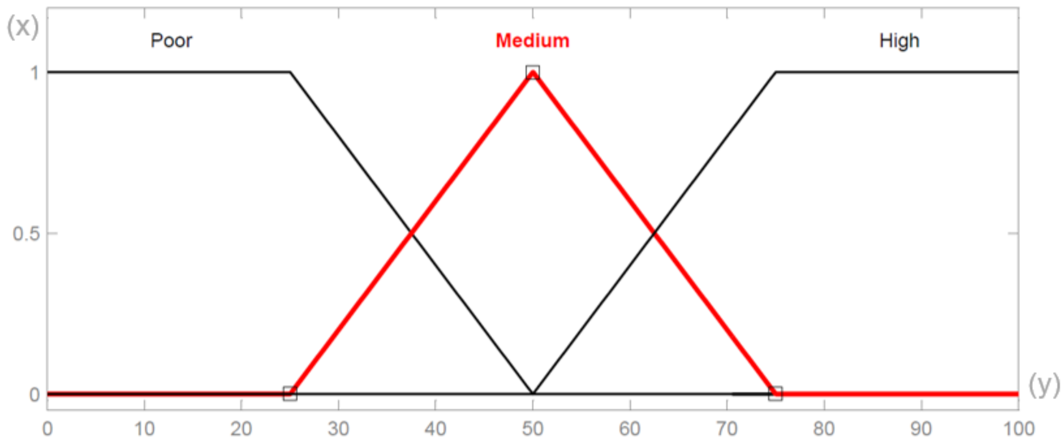


Figure 4. Membership functions for “conscientiousness”

$$\mu Poor[x] = \begin{cases} 1; & x \leq 25 \\ \frac{50-x}{50-25} & 25 \leq x \leq 50 \\ 0; & x \geq 50 \end{cases} \quad (4)$$

$$\mu Medium[x] = \begin{cases} 0; & 25 \geq x \geq 75 \\ \frac{x-25}{50-25} & 25 \leq x \leq 50 \\ \frac{75-x}{75-50} & 50 \leq x \leq 75 \end{cases} \quad (5)$$

$$\mu High[x] = \begin{cases} 0; & x \leq 50 \\ \frac{x-50}{65-50} & 50 \leq x \leq 75 \\ 1; & x \geq 75 \end{cases} \quad (5)$$

2.3.3. Extraversion (E)

Relating to a person's comfort level in interacting with others. The positive characteristics of extraversion individuals are sociable, sociable, group life and assertive. Instead, individuals are introversion. The opposite of extraversion is those who are shy, aloof, timid and reserved. Opennes variables are divided into three sets namely "high", "medium", and "poor" shown in Table 4 and membership functions in Figure 5.

Table 4. Fuzzyfication of the input variable "extraversion"

Input variable	Crisp set	Fuzzy set
Extraversion (Number)	0-50	High
	25-75	Medium
	50-100	Poor

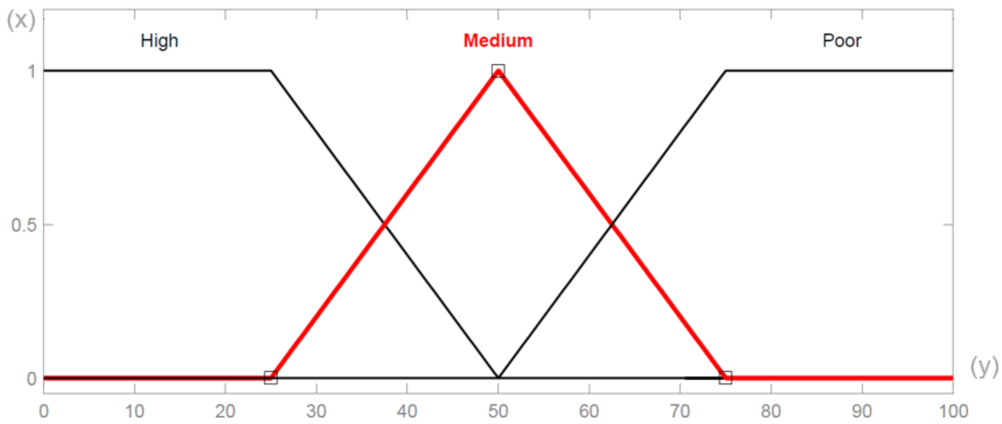


Figure 5. Membership functions for "extraversion"

$$\mu High[x]=\begin{cases} 1; & x\leq 25 \\ \frac{50\text{-}x}{50\text{-}25} & 25\leq x\leq 50 \\ 0; & x\geq 50 \end{cases} \tag{7}$$

$$\mu Medium[x] = \begin{cases} 0; & 25 \geq\ x \geq 75 \\ \frac{x-25}{50-25} & 25 \leq x \leq 50 \\ \frac{75-x}{75-50} & 50 \leq x \leq 75 \end{cases} \tag{8}$$

$$\mu Poor[x] = \begin{cases} 0; & x \leq 50 \\ \frac{x-50}{65-50} & 50 \leq x \leq 75 \\ 1; & x \geq 75 \end{cases} \tag{9}$$

2.3.4. Agreeableness (A)

Agreeableness tends to be more obedient with other individuals and has a personality that wants to evade conflict. His constructive characteristics are cooperative, trusting, kind, warm and soft-hearted and cooperative. The opposite characteristic of this trait is that it is not easy to agree with other individuals because it likes to be resistant, cold and unfriendly. The agreeableness variable is divided into three sets namely "poor", "medium", and "high" shown in Table 5 and the membership function in Figure 6.

Table 5. Fuzzyfication of the input variable "agreeableness"

Input variable	Crisp set	Fuzzy set
Extraversion (Number)	0-50	Poor
	25-75	Medium
	50-100	High

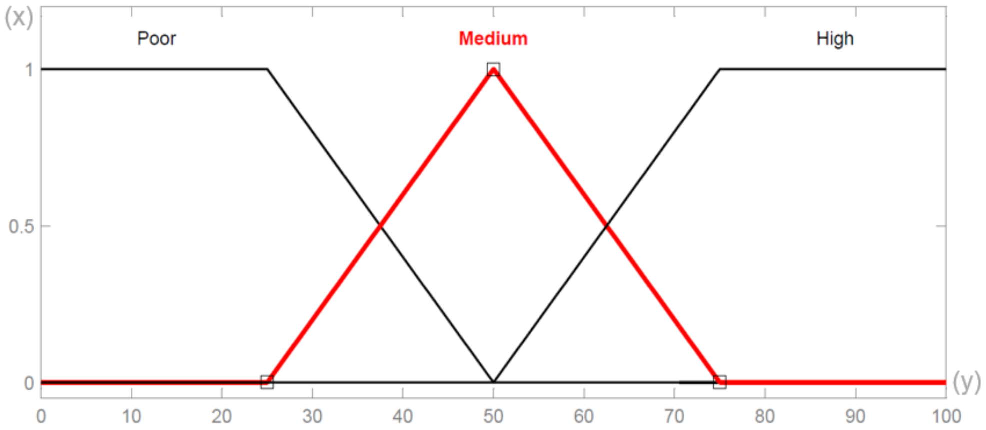


Figure 6. Membership functions for “agreeableness”

$$\mu Poor[x]=\begin{cases} 1; & x\leq 25 \\ \frac{50-x}{50-25} & 25\leq x\leq 50 \\ 0; & x\geq 50 \end{cases} \quad (10)$$

$$\mu Medium[x]=\begin{cases} 0; & 25\geq x\geq 75 \\ \frac{x-25}{50-25} & 25\leq x\leq 50 \\ \frac{75-x}{75-50} & 50\leq x\leq 75 \end{cases} \quad (11)$$

$$\mu Heigh[x]=\begin{cases} 0; & x\leq 50 \\ \frac{x-50}{65-50} & 50\leq x\leq 75 \\ 1; & x\geq 75 \end{cases} \quad (12)$$

2.3.5. Neuroticism (N)

Neuroticism is a person’s ability to survive pressure or tension. The positive characteristic of neuroticism is stated as emotive stability. Emotionally stable individuals tend to be tranquil when facing problems, confident, have a firm stance. While the personality characteristics of neuroticism or negative characteristics are easily panicky, depressed, not confident and easy to change minds. The emotional stability dimension is the positive side. The neuroticism variables are divided into three sets namely “poor,” “medium,” and “high” shown in Table 6 and the membership function in Figure 7.

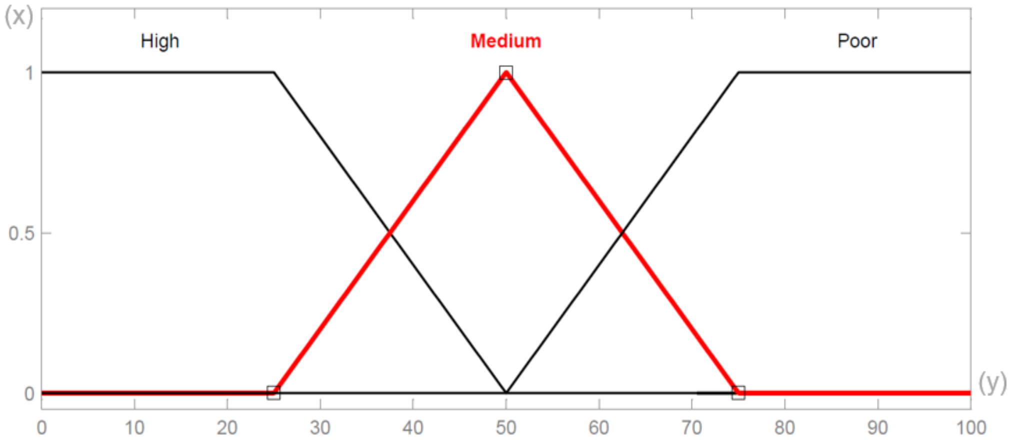


Figure 7. Membership functions for “neuroticism”

$$\mu High[x]=\begin{cases} 1; & x\leq 25 \\ \frac{50\text{-}x}{50\text{-}25} & 25\leq x\leq 50 \\ 0; & x\geq 50 \end{cases} \tag{13}$$

$$\mu Medium[x] = \begin{cases} 0; & 25 \geq\ x \geq 75 \\ \frac{x-25}{50-25} & 25 \leq x \leq 50 \\ \frac{75-x}{75-50} & 50 \leq x \leq 75 \end{cases} \tag{14}$$

$$\mu Poor[x] = \begin{cases} 0; & x \leq 50 \\ \frac{x-50}{65-50} & 50 \leq x \leq 75 \\ 1; & x \geq 75 \end{cases} \tag{15}$$

Table 6. Fuzzyfication of the input variable “neuroticism”

Input variable	Crisp set	Fuzzy set
Neuroticism (Number)	0-50	High
	25-75	Medium
	50-100	Low

2.4. Output variables
2.4.1. Loan (%)

The output of FES is the percentage of the loan. The numerical value will help identify the recommended loan amount such as the minimum loan amount or maximum openness for experience, conscientiousness, extraversion, agreeableness, and neuroticism variables of the prospective debtor as input variables for FES. If the loan value is ≤35, then we can identify a high probability that the prospective debtor gets a minimum loan, but if the output value is more ≥65 then the prospective debtorr will get the maximum loan percentage. The loan output variables are categorized into two fuzzy sets: “minimum” and “maximum”. The trapezoidal curve is used for membership functions on output variables. Table 7 and Figure 8 show this fuzzy set and membership functions for output variables.

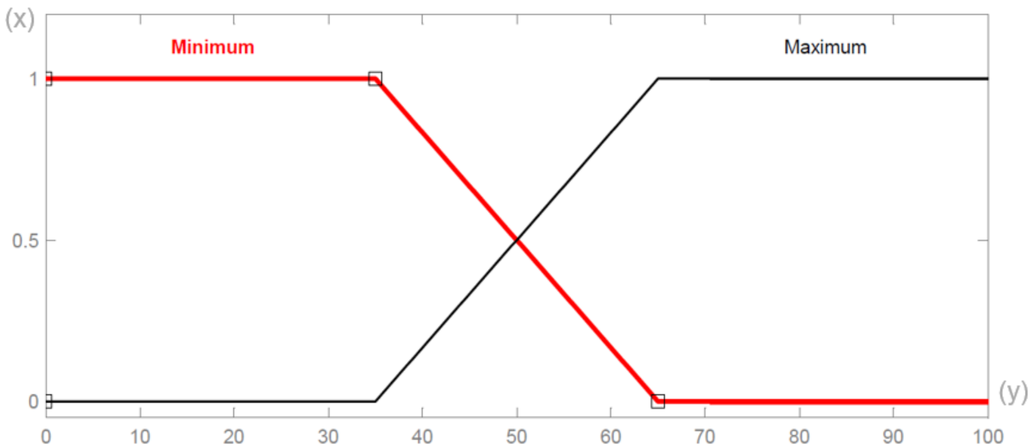


Figure 8. Output variable for “loan” (%)

$$\mu Minimuml[x]=\begin{cases} 1; & x\leq 35 \\ \frac{65\text{-}x}{65\text{-}35} & 35\leq x\leq 65 \\ 0; & x\geq 65 \end{cases} \tag{16}$$

$$\mu Maximum[x] = \begin{cases} 0; & x \leq 35 \\ \frac{x-35}{65-35} & 35 \leq x \leq 65 \\ 1; & x \geq 65 \end{cases} \tag{17}$$

Table 7. Fuzzyfication of the input variable "neuroticism"

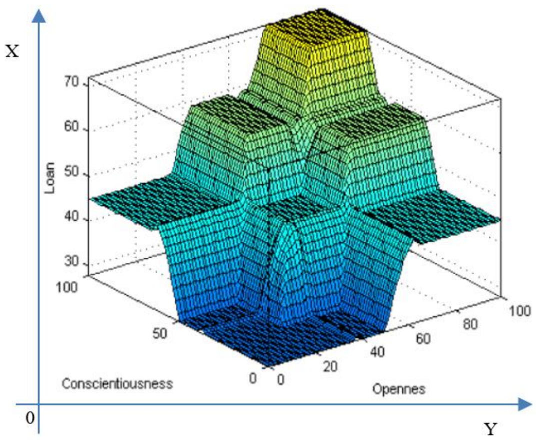
Input variable	Crisp set	Fuzzy set
Loan (%)	0-65	Minimum
	35-100	Maximum

2.4.2. Fuzzy rule base

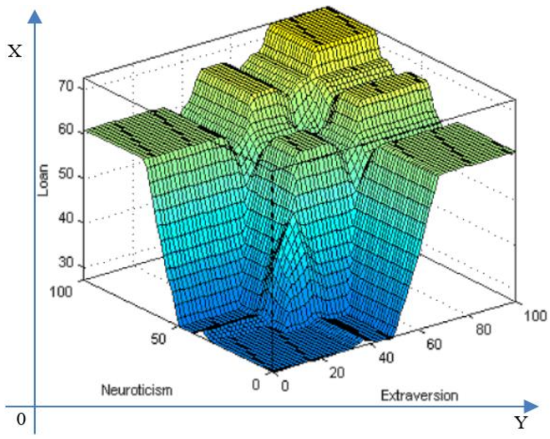
System we developed there are five input variables. Each input has three sets, so the total rule base is calculated based on 3×3×3×3×3 = 243. The rule base is built using the IF-Then function to get the output as a percentage of the loan. We perform an analysis to determine the domain on the output variable. We find the weight of the variable that has an effect on the output. The highest weights were opennes variables of 0.498, extraversioon = 0.315, and agreeableness = 0.187. Based on the value of the weight, we determine the following rules:

[R141]: If Openness = Medium and Conscientiousness = High and Extraversioon = Poor and Agreeableness = Medium and Neuroticism = Poor Then Loan=Maximum (1)
[R144]: If Openness = Medium and Conscientiousness = High and Extraversioon = Poor and Agreeableness = High and Neuroticism = Poor Then Loan=Maximum (1)
[R150]: If Openness = Medium and Conscientiousness = High and Extraversioon = Medium and Agreeableness = Medium and Neuroticism = Poor Then Loan=MINIMUM (1)
[R153]: If Openness = Medium and Conscientiousness = High and Extraversioon = Medium and Agreeableness = High and Neuroticism = Poor Then Loan=Maximum (1)
[R222]: If Openness = High and Conscientiousness = High and Extraversioon = Poor and Agreeableness = Medium and Neuroticism = Poor Then Loan=Maximum (1)
[R225]: If Openness = High and Conscientiousness = High and Extraversioon = Poor and Agreeableness = High and Neuroticism = Poor Then Loan=Maximum (1)
[R231]: If Openness = High and Conscientiousness = High and Extraversioon = Medium and Agreeableness = Medium and Neuroticism = Poor Then Loan=Maximum (1)
[R234]: If Openness = High and Conscientiousness = High and Extraversioon = Medium and Agreeableness = High and Neuroticism = Poor Then Loan=Maximum (1)

Example rule 141 if openness= "medium" and conscientiousness= "high", extraversion= "poor", agreeableness= "medium", and neuroticism= "poor", then based on the rule the percentage of incoming loans is on the set "maximum". Other rules can be spelled out in a similar way. The surface viewer provides a visualization of the rules applied in the proposed system. Our proposed system uses five inputs and one output, so there cannot be an output dependency on all inputs. So, in the surface viewer we've split the output against two input variables by storing some values for the two inputs. Figure 9. Describing the prediction of the magnitude of recommendations based on the acquisition of scores consisting of: Figure 9(a) show 2 surface viewers where the variables used are openness to conscientiousness, and Figure 9(b) neuroticism to extraversion.



(a)



(b)

Figure 9. Surface Viewer useful for viewing mapping images between input variables and output variables (a) surface viewer uses two variables openness and conscientiousness and (b) neuroticism and extraversion as input and loan (%) as output

2.4.3. Defuzzification and mamdani inference engine

Defuzzification is the process of obtaining the exact magnitude of a fuzzy set. In FES, we have used the centroid method to defuzzify using (18).

$$z = \frac{\int \mu C(z).zdz}{\int \mu C(z).dz} \tag{18}$$

For a specific set of input variables such as openness=72, conscientiousness=84, extraversioon=60, agreeableness=68, and neuroticism=84. Next calculate the degree of membership of each variable. The degree of truth (i) of the i-th rule is determined by means of FIS Mamdani by taking the minimum value from several values of the degree of membership. Furthermore, the smallest value is compared and the largest value is taken. Then calculated using the centroid method, then a crisp value is obtained for the loan output. The following steps are shown for the above-mentioned input data:
(1) $Opennes = 72, \mu(Poor) = 0, And\ \mu Medium = 0.12, and\ \mu High = 0.88$
(2) $Conscientiousness = 80, \mu(Poor) = 0, And\ \mu Medium = 0, and\ \mu High = 1$
(3) $Extraversioon = 60, \mu(High) = 0, And\ \mu Medium = 0.6, and\ \mu Poor = 0.4$
(4) $EAgreeableness = 68, \mu(Poor) = 0, And\ \mu Medium = 0.28, and\ \mu High = 0.72$
(5) $Neuroticism = 84, \mu(High) = 0, And\ \mu Medium = 0, and\ \mu Poor = 1$

For the above set of input data, eight rules will come into action and yield:
(1) $\alpha_{141} = \min(0.12; 1; 0.4; 0.28; 1) = 0.12$
(2) $\alpha_{144} = \min(0.12; 1; 0.4; 0.72; 1) = 0.12$
(3) $\alpha_{150} = \min(0.12; 1; 0.6; 0.28; 1) = 0.12$
(4) $\alpha_{153} = \min(0.12; 1; 0.6; 0.72; 1) = 0.12$
(5) $\alpha_{222} = \min(0.88; 1; 0.4; 0.28; 1) = 0.28$
(6) $\alpha_{225} = \min(0.88; 1; 0.4; 0.72; 1) = 0.4$
(7) $\alpha_{231} = \min(0.88; 1; 0.6; 0.28; 1) = 0.28$
(8) $\alpha_{234} = \min(0.88; 1; 0.6; 0.72; 1) = 0.6$
which further provides.

$$\alpha = \max\left(a_{141}, a_{144}, a_{150}, a_{153}, a_{222}, a_{225}, a_{231}, a_{234}\right) \tag{19}$$
$$\alpha = \max(0.12; 0.12; 0.12; 0.12; 0.28; 0.4; 0.28; 0.6) = 0.6$$

Using the value of α=0.6 to get the output value using the centroid method, a loan value of 59% was obtained, where the recommendation value based on the proposal system was lower than the admin recommendation of 70%. Therefore, in this case prospective debtors are advised to be given the loan amount according to the calculation results in the proposal system. We have applied fuzzy logic using MATLAB Software to calculate 25 prospective debtor data for loan amount recommendations.

3. RESULTS AND DISCUSSION

We distribute questionnaires filled in by prospective Debtors. This questionnaire is used to measure the Debtor's personality based on five TBFP variables, namely Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism. The questionnaire was compiled from borrowers who are applying for loans on the P2P Lending platform. Data collection was carried out over a period of 2 months. The test results that have been filled in by 25 prospective debtors using TBFP are shown in Figure 10.

Name	Openness (O)						Conscientiousness (C)						Extraversion (E)						Agreeableness (A)						Neuroticism (N)					
	O1	O2	O3	O4	O5	TO	C1	C2	C3	C4	C5	TC	E1	E2	E3	E4	E5	TE	A1	A2	A3	A4	A5	TA	N1	N2	N3	N4	N5	TN
Debtor 1	100	60	80	80	40	72	100	60	80	100	60	80	20	80	100	20	80	60	60	100	60	60	60	68	80	60	100	100	80	84
Debtor 2	80	60	80	80	100	80	80	80	80	80	80	80	40	60	100	80	60	68	60	80	60	80	60	68	60	60	20	40	40	44
Debtor 3	80	60	100	40	100	76	80	100	80	100	40	80	40	60	60	60	40	52	60	100	60	100	20	68	80	60	40	80	40	60
Debtor 4	100	100	100	100	100	100	100	100	100	100	100	100	20	20	20	20	20	20	100	100	100	100	100	100	20	20	20	20	20	20
Debtor 5	80	80	80	60	80	76	80	80	80	80	100	84	40	40	60	60	40	48	80	80	80	80	80	80	60	60	80	40	40	56
Debtor 6	100	100	100	20	80	80	100	100	100	100	20	84	60	80	40	20	20	44	80	100	20	80	60	68	40	40	40	40	40	40
Debtor 7	60	60	80	80	40	64	80	60	80	80	60	72	60	80	100	80	60	76	60	80	60	80	60	68	40	60	40	60	40	48
Debtor 8	60	80	80	80	80	76	80	80	60	80	60	72	100	60	100	60	60	76	80	80	40	80	40	64	80	60	40	100	80	72
Debtor 9	100	60	100	20	80	72	80	80	100	100	60	84	60	60	100	60	20	60	20	100	20	60	20	44	80	80	100	60	20	68
Debtor 10	80	60	80	40	100	72	100	80	80	100	60	84	60	60	60	40	20	48	80	100	100	80	80	88	80	80	80	80	80	80
Debtor 11	80	60	60	60	80	68	80	100	80	80	60	80	80	60	80	80	60	72	80	100	20	40	40	56	40	60	60	60	20	48
Debtor 12	100	60	100	20	60	68	100	100	100	100	80	96	60	40	40	40	20	40	80	100	80	100	100	92	60	60	100	60	40	64
Debtor 13	100	60	100	40	80	76	80	60	100	100	60	80	40	80	60	20	60	52	80	100	40	40	80	68	80	60	100	80	60	76
Debtor 14	80	80	80	80	60	76	80	40	20	60	80	56	60	60	60	40	20	48	60	100	100	100	60	84	60	60	60	60	60	60
Debtor 15	100	100	100	20	100	84	100	100	80	100	80	92	60	40	60	40	40	48	80	100	80	80	80	84	20	40	20	40	20	28
Debtor 16	100	80	100	20	80	76	100	80	100	100	60	88	60	40	40	20	20	36	100	100	80	100	60	88	60	100	20	60	40	56
Debtor 17	60	80	80	40	60	64	80	80	40	100	60	72	80	60	60	60	60	64	20	80	100	80	20	60	60	60	100	60	80	72
Debtor 18	80	60	60	40	60	60	100	80	80	100	100	92	60	80	80	60	80	72	80	100	40	100	60	76	60	60	100	100	80	80
Debtor 19	100	80	100	20	60	72	100	80	80	80	80	84	80	60	60	80	60	68	60	100	20	80	20	56	20	60	40	40	40	40
Debtor 20	100	60	100	80	80	84	80	60	60	100	80	76	80	60	60	80	20	60	80	80	80	80	20	68	60	40	100	80	40	64
Debtor 21	80	80	100	40	60	72	100	60	80	80	40	72	60	60	80	80	60	68	60	100	20	100	80	72	100	80	100	100	40	84
Debtor 22	60	60	60	80	80	68	80	60	80	80	60	72	40	60	60	40	40	48	80	80	60	80	80	76	40	60	80	80	80	68
Debtor 23	80	80	100	40	100	80	80	80	80	80	60	76	60	60	60	60	60	60	20	100	60	60	60	60	60	60	80	80	40	64
Debtor 24	100	80	100	60	80	84	80	80	100	80	60	80	80	100	40	80	60	72	60	100	80	60	80	76	60	60	100	60	60	68
Debtor 25	100	100	100	20	100	84	100	100	100	100	60	92	20	40	20	40	20	28	100	100	60	20	100	76	20	20	20	20	20	20

Figure 10. TBFP survey filling results

Information:
- Total openness (TO)
- Total conscientiousness (TC)
- Total extraversioon (TE)
- Total agreeableness (TA)

3.1. Total neuroticism (TN) GUI system fuzzy

The proposed system was developed using the fuzzy Matlab graphical user interface (GUI). The input variable uses the principle of the TBFP which consists of five input variables, namely openness for experience, conscientiousness, extraversion, agreeableness, and neuroticism. Data from input variables is processed using FIS Mamdani and produces output in the form of loan percentage recommendations. Figure 10 features a fuzzy system GUI. Based Figure 11, there is bad credit data from prospective debtors ID=1 having an openness value of 72, conscientiousness 84, extraversioons 60, agreeableness 44, and neuroticism 68, so based on the calculation results of the fuzzy system, the loan amount is recommended at 59%. This result is different from the assessment of the admin who approved the loan amount of 70%.

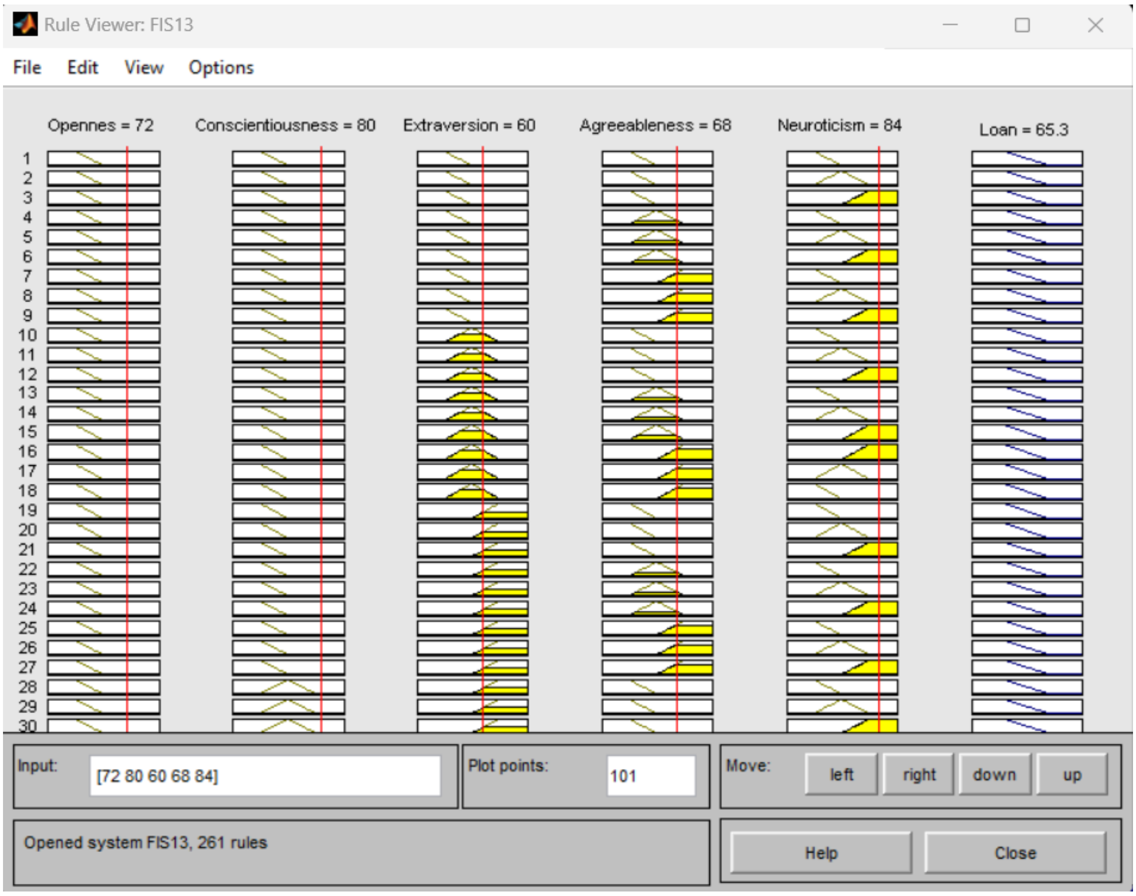


Figure 11. Proposed system with GUI MATLAB

3.2. Evaluation

The evaluation was carried out by comparing the bad credit data from the assessment results from the admin and fuzzy shown in Table 8. The average percentage of loan recommendations given by the admin is 82% of the total bad loans in 25 debtors in February 2023 of IDR 975,000,000. An error in recommendation from the admin resulted in a company loss of IDR 799,500,000. When compared to system recommendations, losses can be reduced to IDR 546,000,000 or 25.6%. We find a pattern based on Table 9 see in Appendix if the extraversion variable ≤38 maka the loan category "minimal". However, if the extraversion is >38, it will consider the agreeableness variable. If agreeableness is ≤82 then the category is "maximal", but if agreeableness is >82 then consider the value of the openness variable. If openness >74 then the category is "minimal", otherwise "maximal". Figure 12 shows a comparison of recommendations from admin and the proposed system with TBFP. Based on the Figure 12, it can be seen that the loan recommendation from the proposal system is lower than the admin recommendation, so that losses due to bad loans can be reduced.

Table 8. Bad loan data based on admin assessment and improve TBFP principle with fuzzy

ID	Name	City	Province	Loan (IDR)	Loan (%) for admin	TBFP with fuzzy (%)
1	Debtor 1	Surakarta	Jawa Tengah	30,000,000	70	59
2	Debtor 2	Purwokerto	Jawa Tengah	50,000,000	70	61
3	Debtor 3	Salatiga	Jawa Tengah	40,000,000	100	59
4	Debtor 4	Tasikmalaya	Jawa Barat	50,000,000	70	26
5	Debtor 5	Cianjur	Jawa Barat	40,000,000	70	68
6	Debtor 6	Senayan	DKI Jakarta	30,000,000	70	55
7	Debtor 7	Pancoran	DKI Jakarta	50,000,000	70	58
8	Debtor 8	Cilincing	DKI Jakarta	30,000,000	100	64.7
9	Debtor 9	Pademangan Barat	DKI Jakarta	40,000,000	70	59
10	Debtor 10	Jelambar Baru	DKI Jakarta	40,000,000	80	70
11	Debtor 11	Kedaung Kali Angke	DKI Jakarta	50,000,000	100	61
12	Debtor 12	Kamal	DKI Jakarta	40,000,000	80	54
13	Debtor 13	Aceh Tengah	Luar Pulau Jawa	20,000,000	90	71
14	Debtor 14	Banda Aceh	Luar Pulau Jawa	30,000,000	70	45
15	Debtor 15	Bangka Barat	Luar Pulau Jawa	40,000,000	80	31.4
16	Debtor 16	Banjarmasin	Luar Pulau Jawa	30,000,000	70	47
17	Debtor 17	Barito Kuala	Luar Pulau Jawa	40,000,000	100	53
18	Debtor 18	Blora	Luar Pulau Jawa	30,000,000	100	70.8
19	Debtor 19	Bolaang Mongondow	Luar Pulau Jawa	60,000,000	90	55
20	Debtor 20	Buol	Luar Pulau Jawa	25,000,000	100	58
21	Debtor 21	Buru Selatan	Luar Pulau Jawa	30,000,000	70	67
22	Debtor 22	Buton	Luar Pulau Jawa	20,000,000	80	61
23	Debtor 23	Puncak	Luar Pulau Jawa	60,000,000	70	53
24	Debtor 24	Nduga	Luar Pulau Jawa	40,000,000	100	71
25	Debtor 25	Puncak	Luar Pulau Jawa	60,000,000	90	27
				Average	82%	56,4%

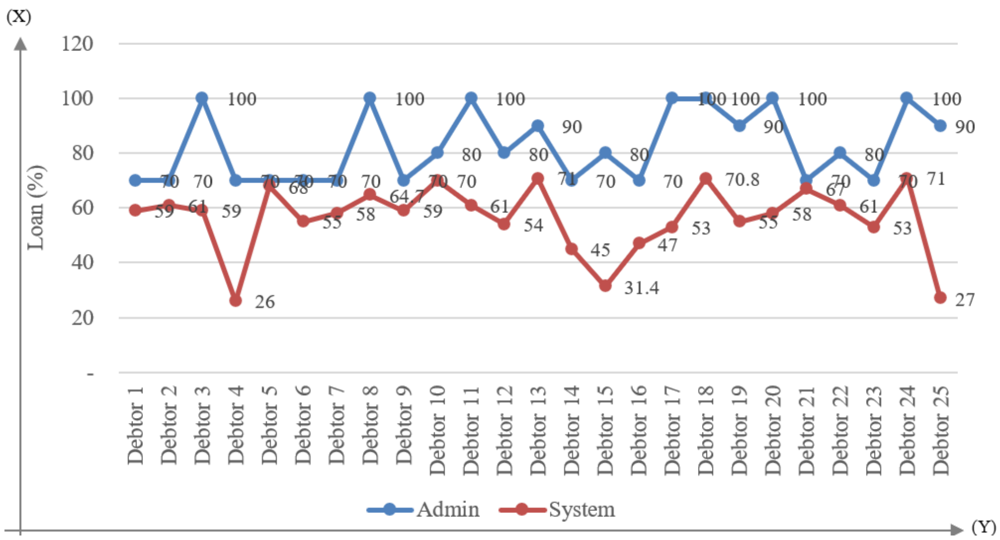


Figure 12. Chart comparing admin recommendations and proposed system with TBFP

3.3. Comparison research

Some related research on the application of fuzzy logic to economics and business for lending is shown in Table 9 see in Appendix. Several studies in Table 9 see in Appendix, report that the application of fuzzy logic can help with financing in the loan granting process. However the application of fuzzy logic combined with TBFP to assess the suitability of prospective online loan debtors in Indonesia has never been reported, therefore this study uses a different approach to loan recommendations using fuzzy-Mamdani logic using the TBFP principle.

4. CONCLUSION

We developed a fuzzy rule-based system using TBFP values as input variables and loan percentages as outputs. We analyze the data to determine the rule base by calculating the weighting of each input variable. We found that the openness variable has a weight of 0.498, the extraversioon variable=0.315, and the agreeableness variable=0.187. Based on the weighting, we create 224 fuzzy rule bases using the IF-Then function. Based on the comparison of admin recommendations and the proposal system, it shows that the application of TBFP on loan amount recommendations can reduce losses due to bad loans by 25%. In addition, we found a pattern, if the variable extraversioon ≤38 maka the loan category "minimal". However, if the extraversioon is >38, it will consider the agreeableness variable. If agreeableness is ≤82 then the category is "maximal", but if agreeableness is >82 then consider the value of the opennes variable. If opennes >74 then the category is "minimal", otherwise "maximal". The results of this study are taken into consideration to be used as input in assessing prospective debtors that are more appropriate so that it has an impact on increasing company revenue. For the community can increase business activities. For the government to help people's economic activities. The proposal system can be used as a reference in the assessment of prospective debtors for banking. Our research still needs to be developed by adding variables such as the financial condition of prospective debtors, psychological values, and loan history. Apart from that, it is necessary to carry out an in-depth study regarding recommendations for loan amounts for bad credit.

APPENDIX

Table 9. Research related to the application of fuzzy to lending *(continue...)*

Authors	Title	Algorithm	Result
[26]	A fuzzy expert system for small business loan processing	Fuzzy	Knowledge acquisition is done using the resources and expertise of the small business development centre. Tests to establish the generality and validity of results are carried out
[27]	Loan risk analyser based on fuzzy logic	Fuzzy	Case study analysis shows consistency and effectiveness of the second approach in taking the right decision
[28]	A fuzzy AHP and DEA approach for making bank loan decisions for small and medium enterprises in Taiwan	Fuzzy-AHP	This article conducts research on small and medium-sized businesses, using the fuzzy analytic hierarchy process (FAHP) to select important indices in loan evaluation, establishes a complete and efficient loan decision-making module and its weights and data envelopment analysis (DEA), and provides effective protection against high loan arrears ratios. A practical case study establishes the effectiveness of the proposed methodology.
[29]	Assessment of the effect on technical efficiency of bad loans in banking industry: a principal component analysis and neuro-fuzzy system	Neuro-fuzzy	ANFIS modelling serves as a tool to unveil the nonlinearity and vagueness inherent in the modelling environment. Within the ANFIS model, technical efficiency is depicted as an output, modelled in relation to factors such as bad debts, profits, and costs. Case studies conducted at Iranian state banks showcase the outcomes of the proposed model, revealing that the influence of bad loans on banks' technical efficiency is not linear but rather exhibits a nonlinear, negative impact.
[21]	Fuzzy and neuro-symbolic approaches in personal credit scoring: assessment of Bank Loan Applicants	Fuzzy	Fuzzy model drew from expert knowledge. Presently, fuzzy rules are rooted in neurulas, a neuro-symbolic rule incorporating both symbolic (production rules) and connectionist (Adaline units) elements. Neurulas maintain the natural and modular qualities of symbolic rules, deriving insights from existing patterns. Assessment indicates comparable performance between the two systems, despite their knowledge bases originating from distinct sources.
[22]	Fuzzy clustering and loan risk prediction	Fuzzy cluster	There are various methods used to support risk decision making. This article discusses the basics of fuzzy grouping methods. Case studies of the use of this method are presented on the prediction of loan risks. Risk prediction plays an important role today.
[30]	Prediction of Chinese financial total loan amount via unbiased grey-fuzzy-Markov chain method.	Fuzzy	This method uses the prediction of the original grey-Markov (GM) framework, eliminating the grey bias present in the original GM (1,1) and improving the anti-jamming ability of the model to cope with random fluctuations in the data. Predictions show that annual investment in China will continue to increase in the next five years with a growth rate of 15%.
[31]	Fuzzy logic-based loan evaluation system.	Fuzzy	The study proposes the existence of a fuzzy logic model for retail loan evaluation. The fuzzy model consists of five input variables such as "income", "credit history", "occupation", "character", and "collateral condition" and one output variable that indicates credit standing. The applicant's credit standing position will be considered as "low", "medium" or "high" based on the membership level for fuzzy output linguistic terms.

Table 1. Research related to the application of fuzzy to lending

Authors	Title	Algorithm	Result
[23]	Fuzzy logic of Zadeh and decision-making in the field of loan.	Fuzzy	The rules on which the decision is based are formulated in the form of logical formulas containing parameters. Some parameters are based on the results of the company's analysis and are predicted. Software systems are currently implemented to support the lending process.
[24]	Loan payment prediction using adaptive neuro fuzzy inference system.	Neuro fuzzy	The system's development aims to provision the finance department in deciding on customer financing plan approvals. The implementation is executed through MATLAB and incorporates the fuzzy logic toolbox, employing functions from the ANFIS modeling system and the customer financing plan assessment system.
[32]	Fuzzy based data mining approach for the loan credibility prediction system in co-operative Banking Sector.	Fuzzy	The main objective of the study is the implementation of fuzzy models that incorporate artificial intelligence approaches to prediction. The experiment was conducted using python programming and selected data from leading banking institutions.
[33]	The development of a fuzzy logic system in a stochastic environment with normal distribution variables for cash flow deficit detection in corporate loan policy.	Fuzzy	Utilizing Mamdani's fuzzy logic system, the calculation of the estimated available cash flow (output variable) is derived from these probabilistic values. The estimation of Cash Flow Adequacy (CFA) serves to identify potential risk scenarios, indicating situations where the company may lack adequate resources to fulfill obligations to financial creditors. All fuzzy logic system calculations are oriented towards future time periods. Rigorous testing and simulation of the fuzzy controller validate its functionality.
[34]	Loan approval in the public-private partnership framework for battery storage power station within an interval-valued intuitionistic fuzzy context.	Fuzzy	Ultimately, the validation of the loan approval evaluation framework is established through case studies conducted in China. Three managerial implications are presented, highlighting the impact of implementing the evaluation index system and the proposed model.
[35]	Loan risk assessment based on Pythagorean FAHP.	Fuzzy-AHP	By comparing the results of traditional analytical hierarchical processes (AHP) and PFAHP, it was found that the method can obtain reliable evaluation results and evaluate personal loans more accurately.
[36]	Study on risk evaluation of intellectual property pledge loan based on fuzzy analytic hierarchy process.	Fuzzy-AHP	The paper focuses on empirical analysis of selected cases, and results in the existence of a fuzzy analytical hierarchical process that can effectively measure the risk of intellectual property mortgage loans, which is conducive to risk assessment and identification of this type of mortgage loan.
[37]	A fuzzy Mamdani approach on community business loan feasibility assessment.	Fuzzy Mamdani	The findings indicated a divergence in the Bank's evaluations, with 78% approval and 22% rejection rates. The average error value across all calculations is then compared to the predefined minimum error value of 5%. As a result, 21 borrowers are deemed eligible for loans. Subsequently, the work proposal is presented to the Bank, serving as material for the analysis and evaluation of each borrower.
[38]	A proposed fuzzy model for reducing the risk of insolvent loans in the credit sector as applied in Egypt.	Fuzzy	The outcomes of the suggested model unveiled a correlation factor of 95.3% between a genuinely reliable payment client and a successful model client. To ensure the precision and validation of the knowledge base, the knowledge model is presented to the credit manager, an expert at the studied bank, who conducts a thorough evaluation of the proposed model's results against the real status of the client.
This research, 2024	BFP with fuzzy approach to feasibility assessment and loan determination for peer-to-peer (P2P) lending	Fuzzy FIS Mamdani	Recommended loan amount using the BFP questionnaire.

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