

Loan Payment Prediction Using Adaptive Neuro Fuzzy Inference System:

A Case Study of XYZ Financial Institution

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Abstract – The financial data in banks and other financial institutions are needed for checking, credit, transaction, etc. In this case, the data must be accurate, complete, and of high quality. The analysis of data could be used to predict a loan repayment and customer credit plan. Meanwhile, data can also be used to perform the classification or clustering to customers, so it is useful for a bank or other financial institution to check the ability of the customer to make loan payments. This paper aims to establish a predictive model based on Adaptive Neuro-Fuzzy Inference System (ANFIS) as an analysis of loan payments financing plan of the customer. It provides an assessment of the possibility of the smooth financing proposed by the customer. The system built is expected to help the finance officer to make decisions on the approval of the financing plan by the customer. Implementation of the overall system is done using MATLAB application utilizing Fuzzy Logic Toolbox. Implementation is carried out in two parts: the function of ANFIS modeling systems and the assessment systems of the customer financing plans.

Keywords – ANFIS; data; Loan; Payment; Prediction

I. INTRODUCTION

Banks and other financial institutions provide a wide range of banking services such as checking, property storage, business transactions, credit, business capital loans, insurance, investment services and others. The financial data contained in banking and other financial institutions are usually very complete, accurate, and high quality. The existence of such data is very useful in addition to the operational process of the transaction that is also a facility perform a variety of data analysis model systematically. For example, designing and building a data warehouse for analysis of multidimensional data [1, 2]. Data warehouses need to be built to banking data [3]. Multidimensional data analysis method can be used to analyze a wide range of property data. For example, to show changes and revenue-based fund owned by the month, or based on region or sector based, or other factors.

Data can also be used to predict a loan repayment and analysis of customer credit plan [4]. Prediction loan payments and analysis of customer credit plan are a very important for banks and other financial institutions. Many factors can strengthen or weaken the ability of loan payments and credit rating of customers [5]. For that data can be utilized to identify important factors that need to be considered and the factors that can be ignored for lending and credit. For example, the ratio of the value of the loan, the loan period, the ratio of payments and revenues, income level of the customer, client education level, the area of residence, credit history or credit, and more.

In addition, data can also be used to perform the classification or clustering to customers. Classification and clustering on clients can be used to identify a target group of

customers and marketing [6]. For example, getting customers with similar behavior in the transaction or make loan payments.

Based on that problem, this paper addressed the problem of the use of Adaptive Neuro-Fuzzy Inference System (ANFIS) to establish a predictive model based on the analysis of loan payments financing plan by the customer [7, 8]. It would only be discussed the issue of financing of XYZ financial institution. For research tool used Matlab with Fuzzy Logic Toolbox to model Adaptive Neuro-Fuzzy Inference System (ANFIS). The aim is to build a model of Adaptive Neuro-Fuzzy Inference System (ANFIS) that has an ability to predict the capability of the financing plan by customers.

II. THE FUZZY SET

A. Classical Set and Fuzzy Set

The classical set is a set with strict limits called crisp. Example, a classic set of real numbers greater than 8 can be expressed in equation (1).

$$A = \{x \mid x > 8\} \quad (1)$$

In equation (1) is a limitation that if x is greater than 8 then x is part of the set A , while for others the value of x isn't part of the set A .

Contrary to the classical set, a Fuzzy set is a set without undefined limits. In the Fuzzy set, the boundary between the member of the set and not a member of the set is gradual and change slowly formed with membership functions that provide flexibility in modeling the expression of linguistic

which is used, for example, cold water or cold temperatures. As an illustration in mathematics, it can be expressed that the set of tall people is taller than 180 cm. If embodied in the equation as in equation (1) i.e. A = "People who are Tall" and x = "Tall", the equation isn't enough to realize the true concept of a tall person. The set of tall people in the classical concept of sets is described as in Figure 1.

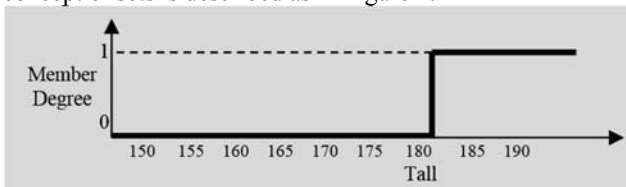


Figure 1. Classical Set of Tall People

If the equation is used, then the tall of 180 cm can be stated that while people with tall of 175 cm or even 179 cm can't be said that the person is tall. There are clear boundaries and a sharp turnaround between a member and not a member of the set. In the Fuzzy set of tall people, the boundary between "member of the set" and "not a member of the set" is gradual and slow changes. In Figure 2, the people with tall or more than or equal to 180 cm is a member of a set of people with a membership degree of 1. While those with less than 180 cm can be a member of a set of people with a different membership degree.

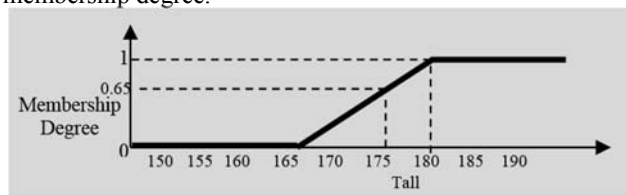


Figure 2. Fuzzy Set of Tall People

In the Fuzzy set, the boundary between "member of the set" and "not a member of the set" is gradual and slow changes. In Figure 2, the people with tall or more than or equal to 180 cm is a member of a set of tall people with a membership degree of 1. While those with less than 180 cm high can be a member of a set of people with a different membership degree. For example, people with tall of 175 cm have a membership degree of 0.65, while those with tall of 164 cm have a membership degree of 0. The membership degree indicates how close to the limit value set for the perfect degree of membership.

B. Additive Method

Additive method is a method of drawing conclusions which solutions of the Fuzzy set obtained from a bounded-sum of all of the Fuzzy set output. The expression of this can be written as equation (2).

$$\mu_{\alpha\beta}[\chi_{\varphi}] \leftarrow \min(1, \mu_{\alpha\beta}[\chi_{\varphi}] + \mu_{\delta\beta}[\chi_{\varphi}]) \quad (2)$$

Where $\mu_{\alpha\beta}[\chi_{\varphi}]$ is a value of Fuzzy solution membership until i-th and $\mu_{\delta\beta}[\chi_{\varphi}]$ is a value of Fuzzy consequent until i-th.

Adaptive networks is a network structure consisting of a number of nodes connected through direct relationships and the characteristic of the overall input and output defined by a set of parameters that can be changed. Each node is a unit process and the relationship between the nodes specifically defines the causal relationship between the vertices. Each node serves as a static node function of the input signal to produce a single output signal from a node and each connection defines the direction of signal flow. Usually, the node function is a function with parameters that can be changed. By changing the parameters on the node function means changing the node function and overall mean change of the nature of the adaptive network. The general architecture of an adaptive network is shown in Figure 3.

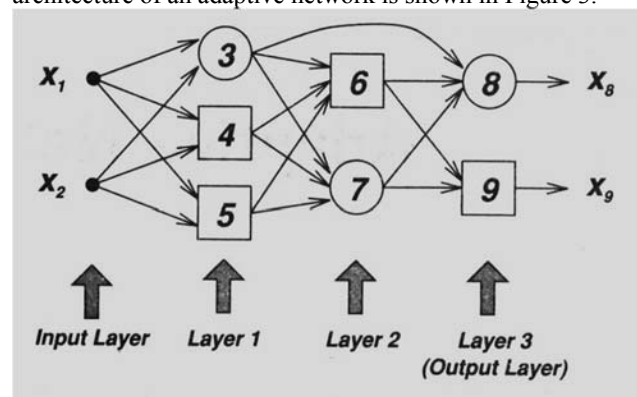


Figure 3. Adaptive Network Architecture

Each node in the adaptive network assumed to define a static mapping from input to output. Particularly, the output of a node depends on input only, not influenced by dynamic or internal conditions in a node. In most cases, the adaptive network is heterogeneous, each node can have a different node function. A set of parameters at each node is called the set of local parameters, and the combination of the set locale is a set of parameters of the whole network. If the parameter on a node isn't empty then the node function depends on the value of these parameters. As shown in Figure 3 symbolized as a box to describe the adaptive node. If the parameter on a node is empty or node has no parameters, then the function concluded nonetheless. While symbolized as circular to describe the fixed node function.

Adaptive networks are generally classified into two categories based on the type of connection that has, namely:

1. Feed-Forward Adaptive Network
2. Recurrent Adaptive Network

The feed-forward adaptive network is shown in Figure 3, marked with an overall output of each node is generated from the input side (left) to the output side (right). If there is a feedback relationship that provides a circular path in the network, the network is a recurrent adaptive network as shown in Figure 4.

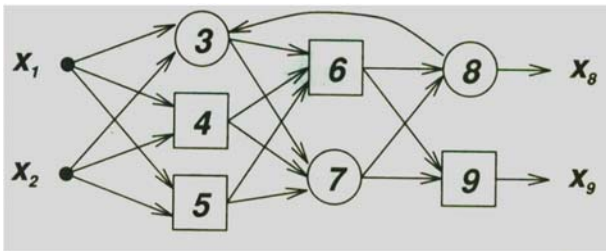


Figure 4. Recurrent Adaptive Network

As seen in the layer, the feed-forward adaptive network there is no relationship between the nodes in a single layer. And the output of the node in a layer will always be connected to the next layer node. In concept, the feed-forward adaptive network is a static mapping between input and output state. A mapping may be a simple linear relationship or non-linearly dependent on the network structure as well as the functionality of each vertex. In building the adaptive network, a linear mapping can be achieved using a data set containing a couple input and output of the desired system of the target system being modeled. This data set is commonly called learning data set. And the procedure to adjust the parameters to improve the performance of the network is called adaptive learning rules or algorithms. Usually, the network performance is measured by the difference between the desired output and the output of the network on the same input conditions. This difference is called the size of the error.

C. ANFIS

For simplicity, it is assumed that the Fuzzy inference system is built with 2 inputs of x and an output of y. Using the Fuzzy model of Sugeno order 1, the general rule set with two Fuzzy rules of IF-THEN are:

Rule 1: IF x is A1 AND y is B1, THEN f1 = p1x q1y + r1

Rule 2: IF x is A2 AND y is B2, THEN f2 = p2x q2y + r2

With p, q, and r are the consequent parameters. If the fire strengths of both these rules are ω_1 and ω_2 , it can be calculated a weighted average using equation (3).

$$f = \frac{\omega_1 f_1 + \omega_2 f_2}{\omega_1 + \omega_2} = \varpi_1 f_1 + \varpi_2 f_2 \quad (3)$$

ANFIS network architecture as shown in Figure 5 consists of layers [9].

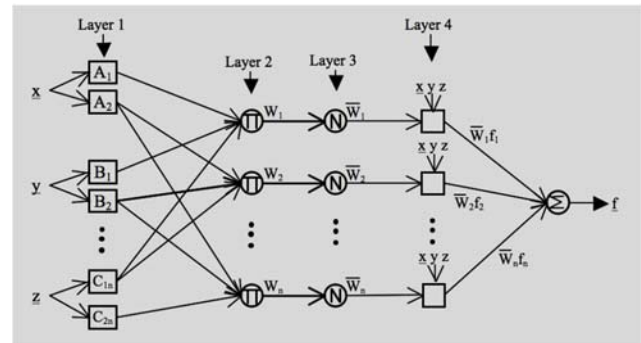


Figure 5. ANFIS Network Architecture

The explanation of these layers could be written as bellow,

- Layer 1, each node of i in this layer is an adaptive node to node function as shown in equation (4).

$$\begin{aligned} O_{1,i} &= \mu_{A_i}(x), & i &= 1, 2 \\ O_{1,i} &= \mu_{B_{i-2}}(y), & i &= 3, 4 \end{aligned} \quad (4)$$

where x (or y) is input to the vertex i and A_i (or B_{i-2}) is a linguistic label associated with a node. In other words, $O_{1,i}$ is the membership level of Fuzzy set A (= A_1, A_2, B_1 or B_2) and define the degree of input x (or y) can meet the assessment A. A membership function of A can take many forms parameterized membership functions e.g. by using the function obtained bell membership function as equation (5).

$$\mu_A(x) = \frac{1}{1 + \left| \frac{x - c_i}{a_i} \right|^{2b}} \quad (5)$$

where $\{a_i, b_i, c_i\}$ is a parameterized set. If a parameter changes the shape of a bell-shaped curve will also change. The parameters on layer 1 are commonly referred to as premise parameters.

- Layer 2, each node in this layer is a fixed node labeled Π , where the output is the product of all the incoming signals as shown in equation (6).

$$O_{2,i} = \omega_i = \mu_{A_i}(x) \mu_{B_i}(y) \quad i = 1, 2 \quad (6)$$

Each output node describes the fire strength of a rule.

- Layer 3, each node in this layer is a fixed node labeled N. Node i-th to calculate the ratio fire strength rules to i-th by the number of total fire strength rules as shown in equation (7).

IV. RESULTS

$$O_{3,i} = \omega_i = \frac{\omega_i}{\omega_1 + \omega_2}, \quad i = 1,2 \quad (7)$$

The output of this layer is called the normalized firing strength.

- Layer 4, each node in this layer is an adaptive node with node function as shown in equation (8).

$$O_{4,i} = \omega_i f_i = \omega_i (p_i x + q_i y + r_i), \quad (8)$$

which ω is normalized firing strength of the layer 3 and $\{p_i, q_i, r_i\}$ are the parameterized set of the node. The parameters in this layer are called the consequent parameters.

- Layer 5, the single mode in this layer is a fixed node labeled Σ which calculates the output is the sum of all the input signal as shown in equation (9).

$$O_{5,i} = \sum_i \omega_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i} \quad (9)$$

III. METHODOLOGY

Implementation of Adaptive Neuro-Fuzzy Inference System (ANFIS) on the prediction of loan payments due to the financing plan analysis established the system that has the ability to provide an assessment of the possibility of the smooth financing proposed by the customer. The system built is expected to help the finance officer to take decisions on the approval of the financing plan by the customer. The system consists of two parts that have functions and different users, namely:

A. ANFIS Implementation

This system serves to produce a fuzzy inference system using ANFIS model with Sugeno’s fuzzy model of order 0 by utilizing a pair of data input/output (I/O) to conduct training on fuzzy inference systems that will be generated [7]. Input-output data needed for training is an accomplished finance data and users of the ANFIS modeling system are experts who know about the ANFIS system.

B. Assessment Systems of Customer Financing Plan

The customer financing plan rating system is a system that will be given to the end user. This system serves to produce the value of the financing plan submitted by customers based on multiple input parameters. Implementation of Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict a loan repayment based on the analysis of the financing plan will be implemented in several stages, including pre-stage process, the data acquisition phase, design phase, the evaluation phase and deployment phase.

In this paper, tests carried out for the entire system is built including ANFIS modeling and customer financing plan assessment systems. Tests carried out sequentially starting ANFIS modeling system testing to obtain the final Fuzzy inference system which is then used in the testing of customer financing plan rating system.

ANFIS modeling system testing conducted to obtain Fuzzy inference systems that have the best performance are marked by obtaining the smallest root mean squared error (RMSE) values in the training process. Tests carried out through training ANFIS with some combination of training parameters include:

- Total of membership function
- Type of membership function
- The number of epochs
- Error Goal

Overall training data obtained from the data acquisition process are stored in files extension in .dat with the overall data amount of 1477. The data is divided into two parts, namely the training data and data checking that each number is 738.

Tests are carried out with ANFIS training with a combination of membership function number parameter of the number of membership functions, the membership function types, the value of epochs and error goal. The first test was carried out for the combination of the parameter values as follows:

- Total of membership function = 3
- Type of membership function = gbellmf
- The number of epochs = 1000
- Error Goal = 0

Depict of ANFIS training interface at the first test can be shown in Figure 6.

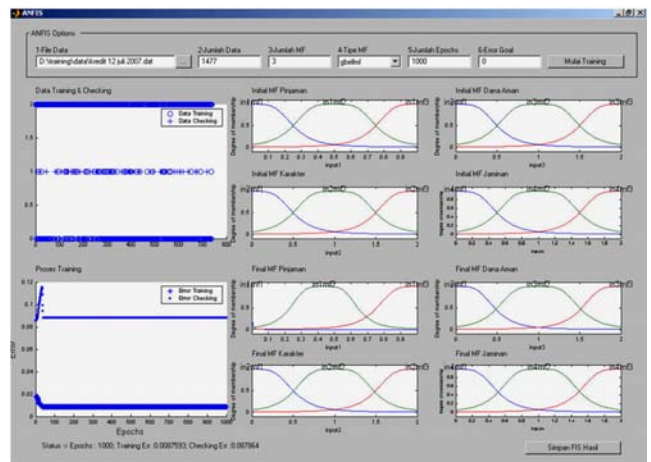


Figure 6. ANFIS Training Interface at The First Test

The first test was carried out to the amount of the membership function of 3 with the type of gbellmf. Total of membership function determines the Fuzzy set amount that would be formed from the universe of discourse for every

existing attribute. Initialization of Fuzzy inference system generates the initial membership function for the first test as shown in Figure 6 can be described as follows:

- Initial Loans MF
The universe of discourse for loan attribute is $U = \{x \mid 0.0007752 \leq x \leq 1\}$. There are three membership functions those are $inmf1$, $inmf2$, and $inmf3$ with equations contained in equation (10), equation (11) and equation (12).

$$inmf1(x) = \frac{1}{1 + \left| \frac{x - 0.0007752}{0.2498} \right|^4}, 0.0007752 \leq x \leq 1 \quad (10)$$

$$inmf2(x) = \frac{1}{1 + \left| \frac{x - 0.5004}{0.2498} \right|^4}, 0.0007752 \leq x \leq 1 \quad (11)$$

$$inmf3(x) = \frac{1}{1 + \left| \frac{x - 1}{0.2498} \right|^4}, 0.0007752 \leq x \leq 1 \quad (12)$$

- Initial Character MF
The universe of discourse for character attribute is $U = \{x \mid 0 \leq x \leq 2\}$. There are three membership functions those are $inmf1$, $inmf2$, and $inmf3$ with equations contained in equation (13), equation (14) and equation (15).

$$inmf1(x) = \frac{1}{1 + \left| \frac{x}{0.5} \right|^4}, 0 \leq x \leq 2 \quad (13)$$

$$inmf2(x) = \frac{1}{1 + \left| \frac{x - 1}{0.5} \right|^4}, 0 \leq x \leq 2 \quad (14)$$

$$inmf3(x) = \frac{1}{1 + \left| \frac{x - 2}{0.2498} \right|^4}, 0 \leq x \leq 2 \quad (15)$$

- Initial Safe Fund MF
The universe of discourse for safe fund attribute is $U = \{x \mid 0 \leq x \leq 2\}$. There are three membership functions those are $inmf1$, $inmf2$, and $inmf3$ with equations contained in equation (16), equation (17) and equation (18).

$$inmf1(x) = \frac{1}{1 + \left| \frac{x}{0.5} \right|^4}, 0 \leq x \leq 2 \quad (16)$$

$$inmf2(x) = \frac{1}{1 + \left| \frac{x - 1}{0.5} \right|^4}, 0 \leq x \leq 2 \quad (17)$$

$$inmf3(x) = \frac{1}{1 + \left| \frac{x - 2}{0.2498} \right|^4}, 0 \leq x \leq 2 \quad (18)$$

- Initial Guarantee MF
The universe of discourse for safe fund attribute is $U = \{x \mid 0 \leq x \leq 2\}$. There are three membership functions those are $inmf1$, $inmf2$, and $inmf3$ with equations contained in equation (19), equation (20) and equation (21).

$$inmf1(x) = \frac{1}{1 + \left| \frac{x}{0.5} \right|^4}, 0 \leq x \leq 2 \quad (19)$$

$$inmf2(x) = \frac{1}{1 + \left| \frac{x - 1}{0.5} \right|^4}, 0 \leq x \leq 2 \quad (20)$$

$$inmf3(x) = \frac{1}{1 + \left| \frac{x - 2}{0.2498} \right|^4}, 0 \leq x \leq 2 \quad (21)$$

The ANFIS training results against the initial Fuzzy inference system for the first test for 1000 epochs with error goal 0 produce the final Fuzzy inference system. The final Fuzzy inference system obtained and then evaluated by providing full data, the training data and checking the data into the final Fuzzy inference system. The final Fuzzy inference system graph for the first test with the overall data is shown in Figure 7.

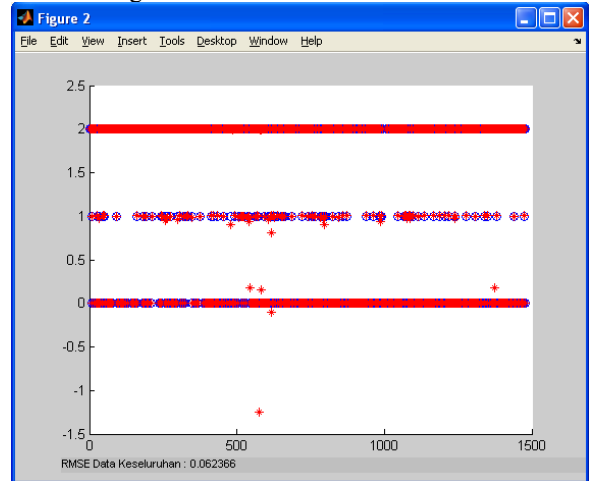


Figure 7. The Final Fuzzy Inference System Graph for The First Test with The Overall Data

While the final Fuzzy inference system graph for the first test with the training data shown in Figure 8.

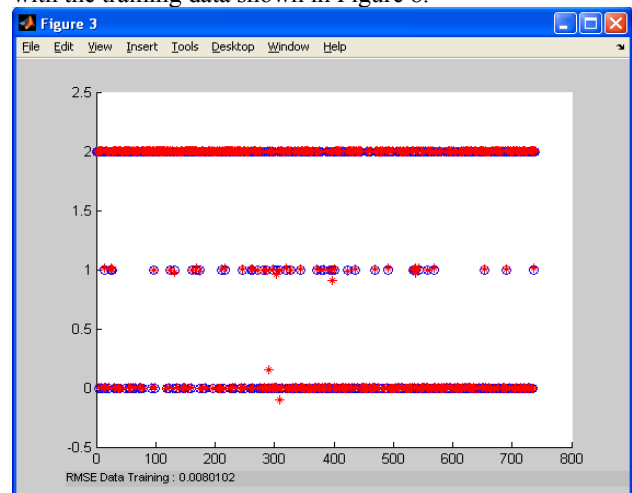


Figure 8. The Final Fuzzy Inference System Graph for The First Test with The Training Data

And the final Fuzzy inference system graph for the first test with checking data shown in Figure 9.

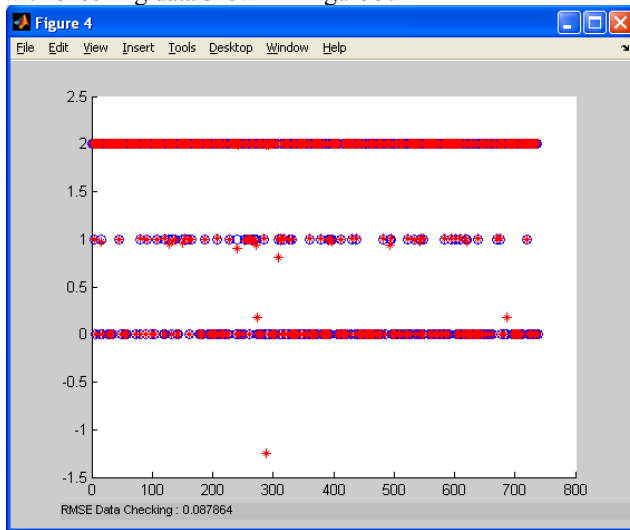


Figure 9. The Final Fuzzy Inference System Graph for The First Test with Checking Data

Root mean squared error (RMSE) is used to measure the difference between the predicted value or a target to the true value obtained from a model. RMSE for the evaluation of the overall data is 0.062366, which means the root of the average squared deviation of the target value and the output value is 0.062366. RMSE for the evaluation of the training data is 0.0080102 which means the root of the average squared deviation of the target value and the output value is 0.0080102. And RMSE for evaluation by checking the data is 0.087864, which means the root of the average squared deviation of the target value and the output value is 0.087864. The smaller the RMSE shows Fuzzy inference system performance is getting better.

V. CONCLUSIONS

An Adaptive Neuro-Fuzzy Systems could be used to build a Fuzzy inference system by utilizing the characteristics of the input-output data pairs that already exist. Characteristics of the data used for the training system will affect the neuro-fuzzy inference system obtained that affects the accuracy of predictions. In addition to the training data, the combination of other parameters in training ANFIS system such as the amount of the membership function, the membership function type will influence the last Fuzzy

inference system obtained which also affects the accuracy of predictions. Root mean squared error (RMSE) is not enough to show a Fuzzy inference system performance, it takes another indicator to show system performance.

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REFERENCES

- [1] A. Dahlan, F. W. Wibowo, "Transformation of Data Warehouse Using Snowflake Scheme Method," *International Journal of Simulation Systems, Science & Technology (IJSSST)*, Vol. 17, No. 35, 2016, pp. 16.1-16.10, doi: 10.5013/IJSSST.a.17.35.16.
- [2] A. Dahlan, F. W. Wibowo, "Design of Library Data Warehouse Using Snowflake Scheme Method: Case Study: Library Database of Campus XYZ," *Proc. of IEEE 2016 7th International Conference on Intelligent Systems, Modelling and Simulation (ISMS)*, 2016, pp. 318-322, DOI: 10.1109/ISMS.2016.71.
- [3] A. Munar, E. Chiner, and I. Sales, "A Big Data Financial Information Management Architecture for Global Banking," *Proc. IEEE International Conference on Future Internet of Things and Cloud (FiCloud)*, IEEE Publisher, Aug. 2014, pp. 385-388, doi:10.1109/FiCloud.2014.68.
- [4] Q. Zhang, C. Wu, and W. Guo, "Listed Commercial Bank Credit Evaluation of Financial Performance Based on AHP," *Proc. IEEE 11th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)*, IEEE Publisher, Aug. 2014, pp. 243-248, doi:10.1109/FSKD.2014.6980840.
- [5] H. A. P. Pérez, J. A. P. Palacio, and C. Lochmuller, "Fuzzy Model Takagi Sugeno with Structured Evolution for Determining Consumer Credit Score," *Proc. IEEE 10th Iberian Conference on Information Systems and Technologies (CISTI)*, IEEE Publisher, June 2015, pp. 1-6, doi:10.1109/CISTI.2015.7170485.
- [6] A. Çalis, A. Boyaci, and K. Baynal, "Data Mining Application in Banking Sector with Clustering and Classification Methods," *Proc. IEEE International Conference on Industrial Engineering and Operations Management (IEOM)*, IEEE Publisher, March 2015, pp. 1-8, doi:10.1109/IEOM.2015.7093731.
- [7] B. Wang, and Z. Mao, "Evaluation of Inputs for Mach Number Prediction Model Based on ANFIS," *Proc. IEEE 2016 Chinese Control and Decision Conference (CCDC)*, IEEE Publisher, May 2016, pp. 2805-2809, doi:10.1109/CCDC.2016.7531459.
- [8] H. Zhou, Y. Wang, W. Wang, T. Li, and H. Yang, "ANFIS Based Credit Analysis for Distribution Management System," *Proc. IEEE 2009 Asia-Pacific Power and Energy Engineering Conference*, IEEE Publisher, March 2009, pp. 1-4, doi:10.1109/APPEEC.2009.4918175.
- [9] C. Chen, R. John, J. Twycross, and J. M. Garibaldi, "An Extended ANFIS Architecture and its Learning Properties for Type-1 and Interval Type-2 Models," *Proc. IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, IEEE Publisher, July 2016, pp. 602-609, doi:10.1109/FUZZ-IEEE.2016.7737742.