Analysis of The Application of Fuzzy Logic and Levenberg-Marquardt in The Calculation of Used Car Prices

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Abstract. In this study using two methods, namely Sugeno Fuzzy Logic and Levenberg-Marquardt methods. The data to be used is data from used Toyota Avanza cars for Medan and surrounding areas. The use of the fuzzy method in this study is based on its superiority in solving vague problems so that it is considered to be suitable for the condition of a used car in which each unit has different conditions. The results of the use of Sugeno fuzzy data obtained will be used as input into the levenberg-marquardt (LM) network which has a fairly good ability to perform calculations, especially to predict an output with a more efficient time. LM produces an output with a small Minimum Square Error (MSE) value of 3.64 in testing with 9 hidden layers. On the other hand, to analyze the resulting error, a comparison is made between networks that have 9 hidden layers, 27 hidden layers and 81 hidden layers with the smallest MSE results obtained on a network with 9 hidden layers.

1. Introduction

Sugeno fuzzy is chosen based on its advantages such as being more accurate and faster when compared to Mamdani in making a prediction [1]. Inputs on sugeno fuzzy will consist of several variables consisting of several member functions. To determine member function, we need to consider the main factors that influence in a case, this time the case will be examined, namely the price of a used car. The price of a used car itself is considered to be very general, so for that reason the writer will focus on the price of a used Toyota Avanza G making from 2012 to 2014. The thing that draws attention from the application of this method is because in determining a used car price several aspects of valuation are needed such as the conditions of the body, the engine, the drive system of the car include the car's wheels and support, the year of which is the Sugeno fuzzy variable input. The rules in Sugeno Fuzzy are based on the results of the application of the knowledge gained from experts in the used car business. The output produced in the form of prices that meet the specified rules.

Levenberg-marquardt (LM) is a combination of the steepest descent method and the Gauss-Newton algorithm which is one of the methods of artificial neural networks [2]. With the basic of the improved backpropagation algorithm to have faster capabilities, especially in the calculation and use of less memory [17]. The use of fuzzy and neural network methods either together or separately to make an estimate or forecast is done on [3 - 12]. The combination of the two methods above is expected to have
more optimal results based on the nature of each. Minimum Square Error (MSE) is used as a measure of the accuracy of the method used.

Input from the LM network itself is in the form of car price data obtained based on the Sugeno fuzzy process. In maximizing the results of the LM process, a comparison of each MSE from the network with different number of hidden layers will be performed. The number of hidden layers that will be formed in each network is 9, 27 and 81 hidden layers.

2. Sugeno fuzzy
This method was introduced by Takagi-Sugeno Kang in 1985 which has almost the same reasoning as the Mamdani method, it’s just that the output (consequent) system is not a fuzzy set, but a linear equation or a constant. To get an output, this method requires 4 stages, namely: formation of fuzzy sets, application of function implications, composition of rules and defuzzify.

Sugeno fuzzy models are of two types, namely zero-order and first-order, for more details as below:

2.1. Zero-order Sugeno fuzzy model
In general, the shape of the zero-order Sugeno fuzzy model is:

\[ IF \ (x_1 \text{ is } A_1) \cdot (x_2 \text{ is } A_2) \cdot \cdots \cdot (x_n \text{ is } A_n) \ \text{THEN} \ z = k \]  

(1)

With \( A_i \) is the fuzzy set for \( i \) as an antecedent, and \( k \) is a constant (decisive) as a consequence.

2.2. Single-order Sugeno fuzzy model
In general the shape of a single-order fuzzy sugeno model is:

\[ IF \ (x_1 \text{ is } A_1) \cdot \cdots \cdot (x_n \text{ is } A_n) \ \text{THEN} \ z = p_1 \cdot x_1 + \cdots + p_n \cdot x_n + q \]  

(2)

Where \( A_i \) is the fuzzy set for \( i \) as an antecedent, and \( p_i \) is an constant for \( i \) and \( q \) is also a constant in consequence. If the composition of the rules using the Sugeno method, defuzzification is done by finding the average value [1].

3. Levenberg-marquardt algorithm
The Levenberg-Marquardt (LM) algorithm is a development of the standard backpropagation algorithm. This method is a combination of Newton's algorithm with Steeps Descent [2] [17]. The equation of the gradient descent method is as follows:

\[ W_{k+1} = W_k - \alpha g \]  

Where \( g \) is a gradient vector, and simplified to \( W_{k+1} = W_k - A_k^{-1} g \)

The form of Newton's equation is:

\[ W_{k+1} = W_k - A_k^{-1} g \]  

(4)

\( A_k \) is the Hessian matrix, where the element is the second derivative of the error against the weigher

\[ A = \begin{bmatrix} \frac{\partial^2 E}{\partial w_1^2} & \frac{\partial^2 E}{\partial w_1 \partial w_2} & \cdots & \frac{\partial^2 E}{\partial w_1 \partial w_n} \\ \frac{\partial^2 E}{\partial w_1 \partial w_2} & \frac{\partial^2 E}{\partial w_2^2} & \cdots & \frac{\partial^2 E}{\partial w_2 \partial w_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 E}{\partial w_1 \partial w_n} & \frac{\partial^2 E}{\partial w_2 \partial w_n} & \cdots & \frac{\partial^2 E}{\partial w_n^2} \end{bmatrix} \]  

(5)

Matrix \( A \) can be written as \( A = 2J^T J \), \( J \) is a Jacobian matrix.
The equation from the Levenberg-Marquardt algorithm is as follows:

$$W_{k+1} = W_k - (J_k^T J_k + \mu I)^{-1} J_k e_k$$

(6)

Where \(e\) = error cumulative vector at the output for all patterns, \(I\) = matrix identity, \(J\) = Jacobian matrix (MxP) output error with N weighting Neural Network, \(\mu\) = training rate, \(w_k\) is the current weight, \(w_{k+1}\) is the next weight, \(E_{k+1}\) is the current total error and \(E_k\) is the last mistake. If the value \(\mu\) (mu) = 0, then the LM method will be the same as the Gauss-Newton method, whereas if the \(\mu\) value is large then the LM method is the same as the backpropagation (steepest descent) method.

4. Simulation result

The data that will be used is the data of used cars in Medan city area, namely the 2012-2014 Toyota Avanza. Based on data that can be directly seen, namely the market price of the car itself. For the price of concern, the lowest price is Rp. 115 million and the highest price of Rp. 140 million. In addition to the price, there are also other data that become Sugeno fuzzy input, namely the condition of the body, engine, wheels and suspension system, the data of which are applied to the rules of the Sugeno fuzzy. Figure 1 shows member function of the body, figure 2 member function of the machine, figure 3 member function of wheels and suspenze systems, and figure 4 member fuction of years. Each of the input variables consists of 3 member functions.

The rules of sugeno fuzzy are as many as 81 rules obtained from deepening with experts in the used car business so that they are expected to provide results that are closer to the actual conditions. For output generated in the form of prices where the variable output consists of 9 member fuctions.

![Figure 1. Membership function of input Body](image1)

![Figure 2. Membership function of the input Engine](image2)

![Figure 3. Membership function of the input Wheels and Suspensions](image3)

![Figure 4. Membership function of the input Years](image4)
Figure 5. Membership function of the output Prices

Figure 6. Rules of sugeno fuzzy

Figure 7. The result of sugeno fuzzy

Figure 6 shows the display rules of sugeno fuzzy which consists of 81 rules. Figure 7 is a display of the results of the sugeno fuzzy based on the rules contained in Figure 6. After the process of searching for the sugeno fuzzy calculation, the resulting data in which 162 data will be input for levenberg-marquardt calculations. In this training the data is divided into 3 parts, namely 98 training data, 32 data validation and 32 data testing. After the training process using the levenberg-marquardt method, the value of MSE (Mean Square Error) is obtained.

The training process itself is carried out three times wherein each training will determine the value of a different hidden layer. In the first hidden layer training used 9, the second hidden layer training was 27 and in the last training used 81 hidden layers.

Table 1. MSE comparison based on the number of hidden layers.

| Hidden Layers | MSE Training | MSE Validation | MSE Testing |
|---------------|--------------|----------------|-------------|
| 9             | 1.38         | 1.24           | 3.64        |
| 27            | 1.19         | 1.98           | 23.48       |
| 81            | 1.34         | 3.53           | 9.62        |

In table 1 can be seen the smallest MSE testing on LM networks with 9 hidden layers and the largest MSE testing on LM networks with 27 hidden layers.

5. Conclusion
The application of sugeno fuzzy in producing used car price data that will be used as training, validation and testing data on the levenberg-marquardt (LM) algorithm results in a relatively small MSE value. Furthermore, to look deeper into training related to LM, changes were made to the number of hidden layers. The results of comparisons with different hidden layers found the overall smallest MSE value
generated on the LM network with 9 hidden layers which amounted to 1.38 in training, 1.24 validation and 3.64 in testing, this value is the smallest MSE layer when compared with two other hidden layers.

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