ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

# DECISION MAKING IMPROVEMENT USING FUZZY NEURAL NETWORK FOR ELECTRIC VEHICLE CONTROLLERS

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**ABSTRACT**

The upcoming need for electric car development is essential in Indonesia. This is because the amount of energy from oil fuel is increasingly limited. To anticipate an energy crisis from oil fuel, especially in motorized vehicles, namely cars, electricity becomes more flexible energy for cars. One of the important parts of an electric car is the control system. This research focuses on the speed control used by electric vehicles so that the speed of the car can change gradually, thereby increasing the comfort and safety of electric vehicles. This makes electric car control system becomes more responsive. The method used in speed control is to combine fuzzy logic and artificial neural networks. The combination of the two methods gives satisfactory results for the artificial neural network model with an MSE value of 0.02566, but it is still not satisfactory for the fuzzy logic model which has an error of 1.732. Improvements to the membership function in the fuzzy logic model need to be done by using more data. In the future, the implementation of the model in the control system needs to be done to get real-time data

**Keywords:** *Electric Car, Control System, Speed Control, Fuzzy Logic, Artificial Neural Network*

## 1. INTRODUCTION

The awareness of the energy crisis has led to the trend of research in transportation leading to the use of electrical energy as a substitute for energy sources that are increasingly depleting [1]. Many studies have been carried out in addressing the use of electrical energy, including the use of electricity as car fuel [2]. Electrical energy is very flexible because it can be converted into motion energy by an electric motor and can be used to move car wheels so that the car can go forward or backward [1].

The electric motor technology commonly used by industry is a direct current motor (DC motor) [3]. DC motors have linear properties so that the speed of a DC motor can be directly adjusted without using additional tools such as an inverter such as an AC motor setting. However, a control system is still needed to control speed [4]. The simple electrical system in DC motors allows the application of control systems. Therefore, a flexible and efficient control system requires the right algorithm to support the formation of an energy-efficient system. PWM (Pulse with Modulation) is a method often used to regulate the rotational speed of DC motors [5]. The PMW technique controls the power supplied to the load by changing the pulse width of the signal sent [6]. This control system allows the average voltage supplied to the motor to be regulated [7]. Then, in building a DC motor control system in an electric car, a regulatory algorithm can be implanted. One of the most widely used regulatory algorithms is artificial intelligence which has very high flexibility [8].

To build artificial intelligence that can be used in a certain method or logic in decision making, based on research that has been done and is widely applied, is fuzzy logic. Where fuzzy logic has been widely implemented in electric motor research. In [9] conducted a study to compare the performance of fuzzy logic and PID (Proportional Integral Derivative) control in the Inverted Gyroscopic Pendulum (GIP) system. This research gives the result that logic has advantages because of its stability and very fast response. Fuzzy logic can also increase the level of precision in the developed robot arm control [10]. Fuzzy logic is also used in power control systems in electric vehicles and produces

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

good performance for dynamic resistance and response to the system [2]. In [11] also explained that fuzzy logic gives good results in maintaining appropriate output and increasing response time in speed implementation. However, the application of fuzzy logic is limited to application systems with limited data so that parameter interpretation tends to experience functional failure. Therefore, artificial intelligence is needed to solve this case.

Besides fuzzy logic, the artificial neural network is artificial intelligence that can be used to solve various existing problems. Artificial Neural Network (ANN) is part of the development of computer science in the field of computational intelligence and is inspired by the workings of the human brain [12]. The ability to handle many variables in a complex form causes the ANN model to be used to solve various problems. Based on the research that has been done, [13] suggests that ANN provides good results in modeling the functions used in closed systems for DC motors. In [14] reported that the ANN model for Brushless DC motors showed good performance with an average error of 0.5 and MSE 1.5. This shows that the application of ANN to electric motors shows satisfactory results. However, in its application, ANN has a complex model with many layers (deep learning) [15], and its interpretation takes longer to produce accurate predictions. Therefore, fuzzy logic is needed to interpret the uncertainty of ANN

Fuzzy logic has advantages in handling uncertainty [16], while ANN can process data and numerical patterns and automatically adjust parameters [17]. Both have a relationship that has the potential to be developed, namely by developing algorithms on the fuzzy and ANN frameworks. The fuzzy logic work system in this study interprets ANN, where ANN finds complex patterns from data without requiring previously established rules. The combination of the two complements each other, but in the literature, especially on electric vehicles, it is still limited.

Therefore, this study aims to optimize speed control on electric vehicles to be more efficient by implementing fuzzy logic and ANN on an electric vehicle prototype. The combination of fuzzy logic and ANN allows for increased control response time to the desired speed.

## 2. RESEARCH METHODE

Research on the electric car control system begins with preparing an electric car prototype, then designing a model that will be used followed by data collection, processing the data with a predetermined model, and then if the model is suitable, the implementation of the speed control model on the car controller is carried out.

In general, this method is depicted in Figure 1.

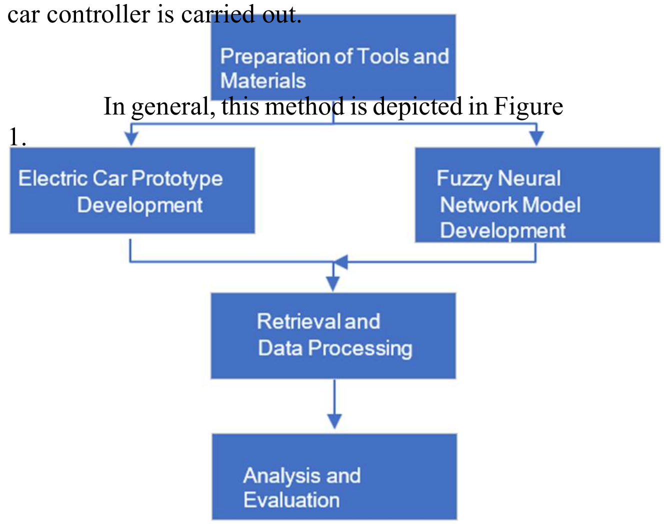


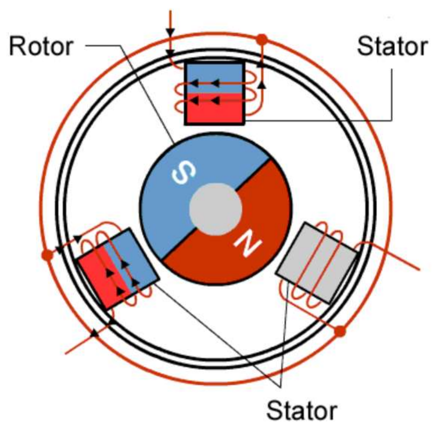

*Figure 1 Research Flowchart*

### 2.1 ELECTRIC MOTOR

The electric motor used in this research is a BLDC motor. BLDC (Brush Less Direct Current) Motor is a type of synchronous motor, which means that the magnetic field generated by the stator and the magnetic field generated by the rotor rotates at the same frequency. The BLDC motor does not slip, unlike what happens in an ordinary induction motor. This type of motor has a permanent magnet on the rotor while the electromagnet on the stator. After that, using a simple circuit (Simple Computer System), the current in the electromagnet can be changed when the rotor rotates [18].

In this case, a BLDC motor is equivalent to a DC motor with an inverted commutator, where the magnet rotates while the conductor remains stationary. In a DC motor commutator, this polarity is changed by the commutator and brush. However, in Brushless DC motors, polarity reversal is performed by the switching transistor to synchronize with the rotor position. Therefore, BLDC motors often incorporate either an internal or external position sensor to sense the actual rotor position, or the position can be detected without a sensor [19].

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195




*Figur 2 BLDC Motor*

### 2.2 FUZZY LOGIC

Fuzzy logic is based on the first fuzzy set introduced by Lotfi A. Zadeh to provide an alternative to definite sets. Fuzzy logic is used to solve problems that are vague and ambiguous. In a controller that uses fuzzy logic, there are several components, namely the fuzzification module, fuzzy rule base, fuzzy inference engine, and defuzzification module [20]. The system is depicted in Figure 3

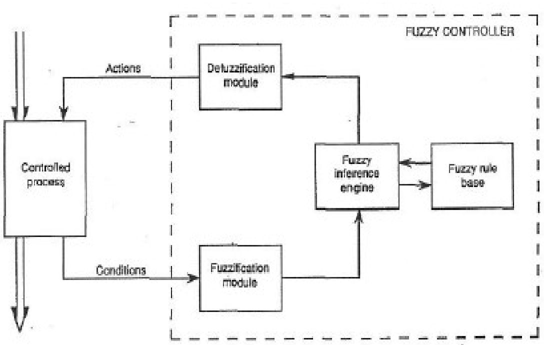



*Figure 3 Fuzzy Controller System*

### 2.3 ARTIFICIAL NEURAL NETWORK

Artificial Neural Network is a model to represent an imitation of the human brain [21]. This model imitates human learning that can adapt to the information it receives and seeks to decide something based on the learning outcomes. Currently, the use of artificial neural networks has been widely used in the industry. These uses include forecasting, classification, and pattern recognition. ANN has been studied extensively and applied successfully to various areas, such as automotives [22]. It may take some time to learn an abrupt massive change but they are effective in adjusting to the constantly changes in information [23]. One of the most widely used artificial neural network models is MLP (Multilayer Perceptron) [21]. The components of the MLP are input, weight, bias, activation, and output functions. In general, MLP can be seen in Figure 4

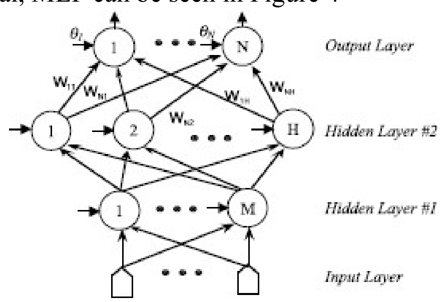



*Figure 4 Multilayer Perceptron Model*

In the MLP model, there are at least 3 neuron layers, namely the input layer, hidden layer, and output layer. The input layer is a layer containing neurons that represent the input. The output layer is a layer that contains neurons representing the output. The hidden layer is a layer that will be trained to form a model that connects the input layer and the output layer.

## 3. ELECTRIC CAR SPEED CONTROL MODEL

The electric car control model involves various interrelated components. This relationship can be seen in Figure 5. These components include electric car pedals, fuzzy systems, neural network systems, controllers, and speed control. When the electric pedal is pressed by the user, the resulting output, namely voltage, and current, becomes the input for the ANN model. The result of ANN processing in the form of reference speed is then entered into the fuzzy logic model. The results of the fuzzy logic model are then used as input to the DC motor to produce speed for the electric car.

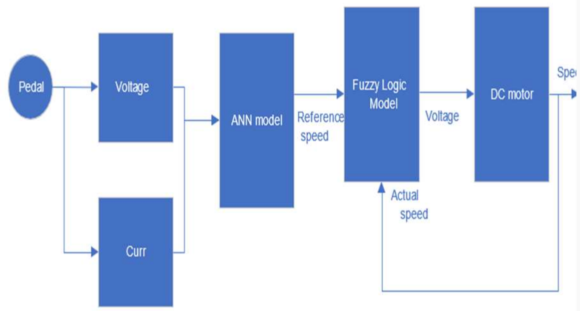



*Figure 5 Model Electric Car Speed Control*

### 3.1 ARTIFICIAL NEURAL NETWORK MODEL

The design of the artificial neural network model built for this model can be seen in Figure 6. In this design, it can be seen that the MLP model used has 1 input layer, 1 hidden layer, and 1 output layer. The number of hidden layers of 1 is determined according to research conducted that 1 hidden layer is sufficient to represent many functions [24]. In [24] also stated that the activation function used in the input and output layers is generally purelin. In the hidden layer, the activation function used is tansig.

$$\text{purelin}(x) = x \quad (1)$$

$$\text{tansig}(x) = \frac{2}{(1+e)^{-x-1}} \quad (2)$$

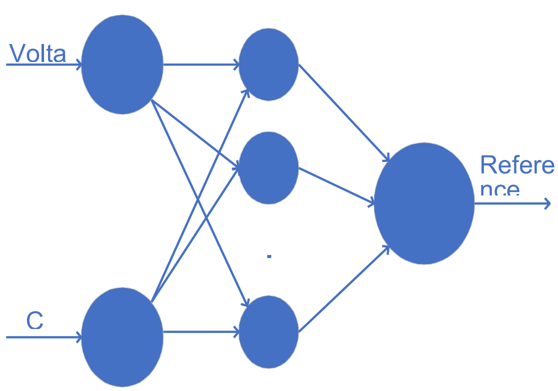



*Figure 6 Artificial Neural Network Model*

### 3.2 FUZZY LOGIC MODEL

The fuzzy logic model in the Speed Control System gets input from the previous ANN model. The fuzzy logic model used in this controller uses input, namely the reference speed and actual speed. The combination of reference and actual speed is processed by fuzzy logic to produce a voltage output that is entered into the DC motor model. The fuzzy logic model developed can be seen in Figure 7.

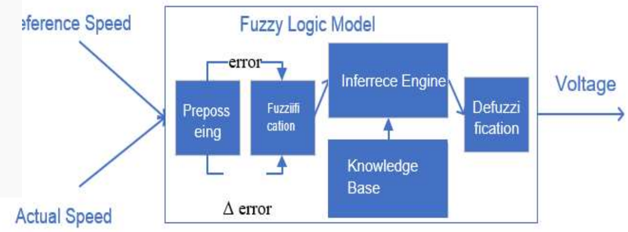



*Figure 7 Fuzzy Logic Model*

In the prepossessing stage, the input in the form of reference speed (ωr) and actual speed (ωa) is processed into error value/e (the difference between reference speed and actual speed) and Δerror/Δe (the difference between errors). The processing is based on equations 3 and 4 [11].

$$e(t) = m_r(t) - m_a(t) \quad (3)$$

$$Ae(t) = e(t) - e(t-1) \quad (4)$$

The fuzzification stage uses a predefined fuzzy set. The fuzzy set used is triangular because even though it is simple, it can represent real conditions. The triangular set has the advantage of being fast in its calculations so that it is suitable for use in control systems that need speed. In this set, 5 values are used in each input variable, namely: PL (positive large), PS (positive small), ZE (Zero), NS (negative small), NL (negative large). The form of each set refers to [2] and can be seen in Figure 8


*Figure 8 Fuzzy Set Of Input Variables*

The fuzzy logic model developed has a rule base which is presented in Table 1 which refers to [11].

Journal of Theoretical and Applied Information Technology
15th June 2025. Vol.103. No.11

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

*Table 1 Basis Of Rules*

| Δ error<br>error | NL | NS | ZE | PS | PL |
|---|---|---|---|---|---|
| **PL** | VH | VH | M | ZE | ZE |
| **PS** | H | M | L | ZE | ZE |
| **ZE** | VH | H | M | L | ZE |
| **NS** | VH | VH | H | M | L |
| **NL** | VH | VH | VH | H | VH |

Based on these rules, the inference is made using the IF production rules ... THEN... The example in the first line: IF e is PL and Δe is NL then the output is PL. In the research, the number of rules obtained is 25 rules.

From the results obtained from all these rules, defuzzification is then carried out using the provisions in Figure 9. The defuzzification results produce the voltage value used in the DC motor.

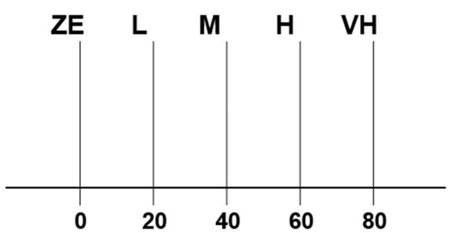



*Figure 9 Output Fuzzy Logic Model*

## 4. RESULTS AND PROCESSING

The data that has been taken, regarding the input voltage, input current, reference speed, and output voltage, is then normalized so that the data values are uniform from values of -1 to 1 for ANN. From this data, then divided, 70% becomes the training data set, and 30% becomes the test data. The data used to conduct training is 7 pieces and then processed using Scilab with the neural network module to get the learning outcomes network that will be used for the next stage. The training was conducted using a learning rate parameter of 0.01; maximum epoch 1000; and the tolerable limit for MSE is 10-5. The training process in Scilab is depicted in Figure 10.

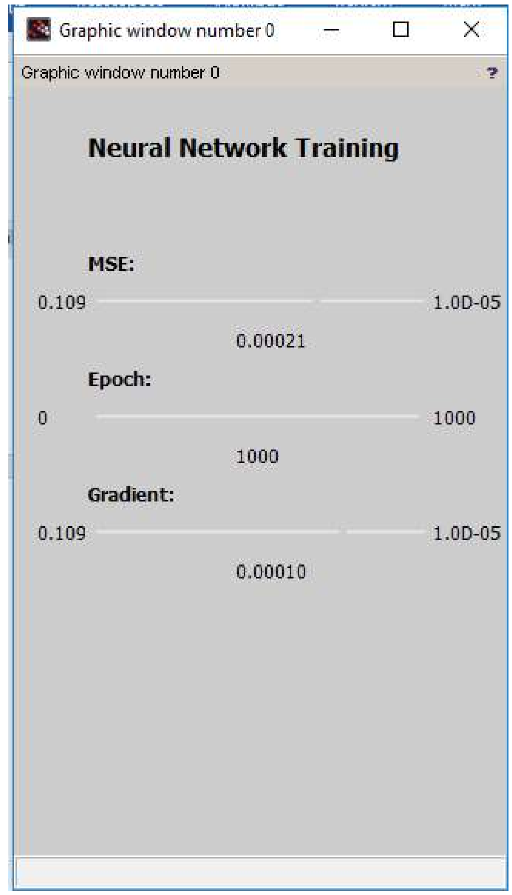



*Figure 10 Ann Training Process*

At this training stage, a search for the right number of neurons for the hidden layer is also carried out so that the smallest MSE value is obtained. The results of the search for the number of neurons are in Table 2. After the number of neurons in the hidden layer was found, the ANN network was tested. The output of the ANN is then normalized by returning the interval to the original value. This output in the form of a reference speed is then used as input to the Fuzzy Logic model along with the actual speed of the motor.

*Table 2 Neuron Search Results*

| Number of Neurons | MSE |
|---|---|
| 3 | 0.03564 |
| 4 | 0.04378 |
| 5 | 0.02566 |

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

| | |
|---|---|
| 6 | 0.03487 |
| 7 | 0.03085 |

The reference speed and actual input into the fuzzy logic are then calculated for the error and error values. The two values are then entered into the fuzzy logic model that has been developed using Scilab with the Fuzzy Toolbox module, namely sciFLT. The results of the implementation of Scilab can be seen in Figure 11.

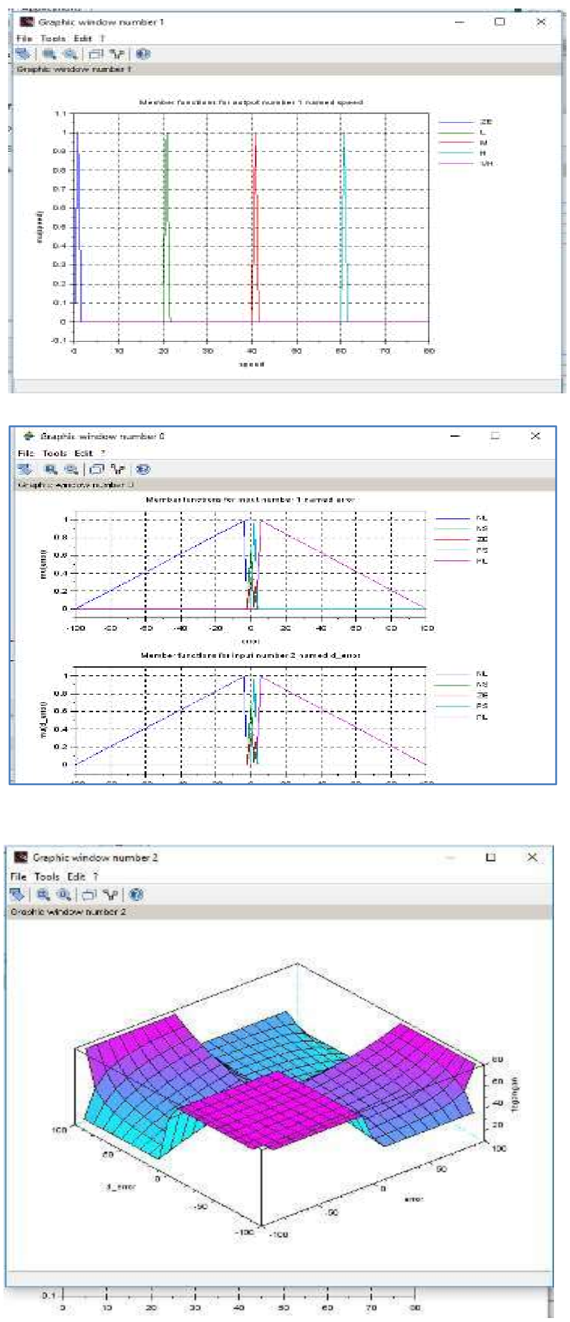



*Figure 11 Results Of Fuzzy Logic*

*Implementation In Scilab*

## 5. MODEL TESTING AND ANALYSIS

Based on the results obtained in the development of an electric motor speed control model, it is found that the architecture that best provides the smallest MSE is [2 5 1] which means 2 neurons in the input layer, 5 neurons in the hidden layer, and 1 neuron in the output layer. The MSE generated from the network architecture is 0.02566. Both smaller and larger numbers of neurons give greater MSE results. This means that the ANN network that provides the best model for this data is the number of neurons in the hidden layer of 5 neurons.

From the ANN model results, the test result data is unnormalized and entered into the fuzzy logic model. From the output generated in the fuzzy logic model, it is found that the average error generated from the model is still quite large, namely 1.732. This large error resulted from the mismatch of the existing membership function in the Fuzzy logic model. Therefore it is necessary to conduct a study of the membership function so that the results obtained are better. Another problem is that the actual speed obtained by the current model has not been obtained from the real condition of the motor. This causes the results do not provide satisfactory results.

## 6. DISCUSSION

Neural networks can cope with very complex interactions, they can easily model data which is too hard to model with conventional methods such as traditional approaches fail [23]. As neural networks can cope with very complex interactions they can easily model data which is too hard to model with conventional methods such as inferential statistics or programming [23]. ANN usually are complex systems that need a lot of computing power in order to function properly [25].

## 7. CONCLUSION AND FUTURE WORKS

The speed control system model in an electric car is built using fuzzy logic and an artificial neural network which is developed by including several inputs, namely current, voltage, and previous speed. The resulting model gives an MSE value of 0.02566 for the artificial neural network model and the results from the fuzzy model give an error of 1.732. To reduce errors in the fuzzy model, it is necessary to implement the model developed in the electric motor

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

control system so that it gets more real-time training data results. Further research could integrate fuzzy logic with other methods such as genetic algorithms, and important to be studied about programming fuzzy neural network architecture in embedded systems.

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