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doi:10.15199/48.2022.02.47

Application of Artificial Neural Network for Speed Control of BLDC Motor 90KW in Electrical Bus

***Abstract**. There are many research on electric vehicles to reduce environmental pollution due to vehicles that use fossil fuels. The advantages of using a BLDC motor are high efficiency, high torque, reduced noise, long lifetime, and easy maintenance. Using of BLDC motors in electric vehicles is sometimes not optimal due to varying set points and presence of loads. Then a speed motor is needed to be controlled so the motor can work properly. In this research using the Artificial Neural Network (ANN) method. The ANN on this speed controller is practical as a 3-phase inverter input voltage control so the speed of BLDC motor can match the set point. In the simulation in this research, controlled based ANN is applied to electric buses with large torque, from the simulation it can be seen that Controlled based ANN can work well.*

Streszczenie**. Istnieje wiele badań dotyczących pojazdów elektrycznych mających na celu zmniejszenie zanieczyszczenia środowiska przez pojazdy wykorzystujące paliwa kopalne. Zalety stosowania silnika BLDC to wysoka sprawność, wysoki moment obrotowy, obniżony poziom hałasu, długa żywotność i łatwa konserwacja. Stosowanie silników BLDC w pojazdach elektrycznych czasami nie jest optymalne ze względu na różne nastawy i obecność obciążeń. Następnie konieczne jest sterowanie prędkością silnika, aby silnik mógł działać prawidłowo. W badaniach wykorzystano metodę Sztucznej Sieci Neuronowej (ANN). SSN na tym regulatorze prędkości jest praktycznym sterowaniem napięcia wejściowego falownika 3-fazowego, dzięki czemu prędkość silnika BLDC może być zgodna z wartością zadaną. W symulacji w niniejszych badaniach, kontrolowany SSN jest stosowany do autobusów elektrycznych o dużym momencie obrotowym, z symulacji widać, że SSN w oparciu o sterowanie może dobrze działać.* (Zastosowanie sztucznej sieci neuronowej do sterowania prędkością silnika BLDC 90KW w autobusie elektrycznym***)

Keywords: Brushless DC Motor (BLDC), Artificial Neural Network (ANN), Electric Vehicle.
Słowa kluczowe: silnik bezszczotkowy BLDC, sztuczne sieci neuronowe, pojazdy elektryczne

Introduction

Along with time, fuel prices are increasing, and many vehicles use fossil fuels which can cause environmental pollution and have an impact on human health. Therefore, an environmentally friendly energy source and efficient vehicle design are needed. Electric bus is one solution to overcome the problem of air pollution. Electric bus can be used as environmentally friendly public transportation so it can help to reduce air pollution. The electric motor that is often used in electric bus/electric vehicle is DC motor because it is easy to control the speed and has a lot of speed variations.

Brushless DC motor is a type of DC electric motor that does not use brushes so that the commutation system is carried out electrically. Without brush, it can reduce problems such as mechanical friction that usually occurs in DC motors that use brushes [1]. BLDC motors are widely used in industry because of their high efficiency and high reliability. In addition, the use of BLDC motors has advantages such as simple construction, does not cause noise, easy maintenance, and has a long lifetime [2]. The use of BLDC motors on electric bus/electric vehicles cannot be separated from the various loads and set points. Then a speed controller is needed to maintain the speed of the BLDC motor in accordance with the set point.

Several methods have been used to adjust the speed of BLDC motors such as PID Controller and Fuzzy Logic. In the use of the PID Controller, it has a simple structure but has not been able to produce a fast response under dynamic load conditions and varying set points. While the Fuzzy Logic can produce a dynamic response, but it takes a long time because of the complex fuzzification and defuzzification process [3-4]. Based on these conditions, this research will design a BLDC motor speed control using the Artificial Neural Network (ANN) method. Artificial Neural Network (ANN) is a method which work process resembles the neural network of the human brain. The Artificial Neural Network (ANN) method has high characteristics in learning of various information.

Basic Theory

A. BLDC Motor

BLDC motor is one type of synchronous motor. This shows that the magnetic field generated by the stator and the magnetic field generated by the rotor will rotate at the same frequency. BLDC motors do not experience the slip that is common in induction motors [5]. BLDC motor is a permanent magnet motor that has a trapezoidal back EMF. This switching on the BLDC motor uses six switching components on a three-phase inverter to activate two phases of the BLDC motor simultaneously while the third phase will be floating. The inverter switching algorithm uses the rotor position that obtained from three Hall Effect sensors on the stator which are installed at 120 degrees from each other electrically. [6]

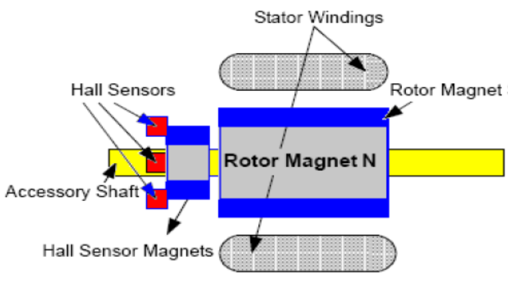

Fig 1. BLDC Motor Construction

Figure 1 shows the BLDC Motor Construction [7]. The rotor in a BLDC motor consists of one or more strong permanent magnets and a fixed stator winding. The rotor is formed from permanent magnets and can change from two to eight pairs of poles with alternating North (N) and South (S) poles. The stator of a BLDC motor consists of a stack of steel laminates with the windings deposited inside the slot. Static stator windings use three phases, where there are three separate voltages connected to different windings. It is often found that the stator winding on BLDC motors is connected in a star (Y) connection configuration. Each winding is assembled with various coils which are interconnected to obtain a winding. More coils will be stored in the slots and connected to each other to form a winding. Each of these windings is distributed on the periphery of the stator to form an even pole. The BLDC motor will detect the position of the rotor or the position of the magnetic poles to generate a signal which is used to control electronic switching.

Commutation in a BLDC motor is helped by using an electronic circuit. There are two methods to control the commutation of BLDC motors, i.e., with sensors and without sensors (sensorless) [5]. To control commutation with sensors, information about the position of the rotor is needed to determine the turn of the switch from the inverter to be connected to the stator. The stator coil will be sourced sequentially according to the position of the rotor inside so that it can drive the motor. Hall Effect Sensor is sensor that used to detect the rotor position. Three Hall sensors will be placed inside the motor with a distance between Hall sensors of 120 degrees [8]. Each Hall sensor will provide information in the form of a High or Low signal according to the polarity of the rotor magnetic poles. The output of the Hall sensor will be used to determine which switch is connected to the stator for source power. In sensorless control, the commutation of the BLDC motor can be controlled using a backemf signal instead of using a Hall sensor. By using this method, the Hall sensor installed in the motor can be removed to simplify the construction of BLDC motor.

Modeling of brushless DC motor assumes that the stator is connected Y, the resistance of each phase is equal, the switching component of the inverter is ideal, and iron core losses including eddy current losses and hysterical losses are ignored [9-10].

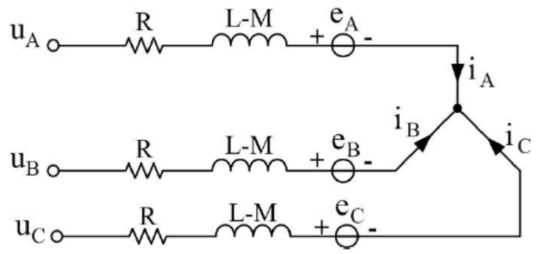

Fig 2. Equivalent Circuit of BLDC Motor

In this equivalent circuit, the current law applies,

(1) $$i_A + i_B + i_C = 0$$

Then the equation can be simplified to,

(2) $$u_A = Ri_A + (L - M)\frac{di_A}{dt} + e_A$$

So, the equation of these phase voltage matrix on each BLDC motor stator coil is as follows:

(3)
$$\begin{bmatrix} u_A \\ u_A \\ u_A \end{bmatrix} = \begin{bmatrix} R & 0 & 0 \\ 0 & R & 0 \\ 0 & 0 & R \end{bmatrix} \begin{bmatrix} i_A \\ i_A \\ i_A \end{bmatrix} + \begin{bmatrix} L-M & 0 & 0 \\ 0 & L-M & 0 \\ 0 & 0 & L-M \end{bmatrix} \frac{d}{dx} \begin{bmatrix} i_A \\ i_A \\ i_A \end{bmatrix} + \begin{bmatrix} e_A \\ e_A \\ e_A \end{bmatrix}$$

While the matrix equation for the phase voltage is obtained from reduction of the voltage between the phases:

(4)
$$\begin{bmatrix} u_{AB} \\ u_{AC} \\ u_{CA} \end{bmatrix} = \begin{bmatrix} R & -R & 0 \\ 0 & R & -R \\ -R0 & 0 & R \end{bmatrix} \begin{bmatrix} i_A \\ i_A \\ i_A \end{bmatrix} + \begin{bmatrix} L-M & M-L & 0 \\ 0 & L-M & M-L \\ M-L & 0 & L-M \end{bmatrix} \frac{d}{dx} \begin{bmatrix} i_A \\ i_A \\ i_A \end{bmatrix} + \begin{bmatrix} e_A - e_B \\ e_B - e_C \\ e_C - e_A \end{bmatrix}$$

where, *u*A, *u*B, *u*C is a phase voltage *A, B,* and *C. R* is a stator resistance, *L* and *M* is self-inductance and mutual inductance. *i*A, *i*B, *i*C is phase current *A, B, and C. e*A, *e*B, *e*C is phase back emf voltage *A, B,* and *C.*

B. Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a method whose work process resembles the neural network of the human brain that can transmit information in the form of computer language. This method is widely used because of its high characteristics in studying characteristic and non-linear mapping of various inputs and outputs. The advantages of using ANN i.e. it can process data that has never been trained by ANN based on what has been obtained during learning, be able to work even if an error occurs, can learn from the data provided and produce a mapping relationship between input and output. The structure of the ANN consists of 3 layers, there are input layer, middle/hidden layer, and output layer. The input layer consists of information to be classified. The middle layer is not an input layer nor an output layer, but a hidden layer that contains the sum of the products from the previous inputs, weights between layers, and activation function. In hidden layer, number of layers and number of neurons is uncertain and requires experimentation to decide how many levels of hidden layer the ANN can work well for a particular model [11].

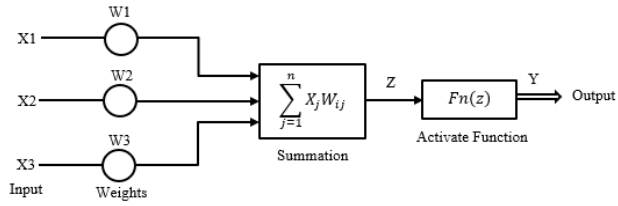

Fig 3. Structure of ANN

In Fig 3. X1, X2, and X3 as an input values from ANN. W1, W2, and W3 as weights values between neuron. The summation function of ANN is as follow:

(5) $$Z_j = \sum_{j=1}^{n} X_j W_{ij}$$

Wij is the weight of jth input of ith cell. The activation function Fn(Z) is applied after summation function to get the exact output. The weights of connection between neurons are modified by supervised learning method. In supervised learning method, outputs are compared with desired inputs. Error is sent back to system. Based on error, weights are adjusted many a times for desired control of network [11]. In this research using Levenberg Marquardt algorithm for weight training.

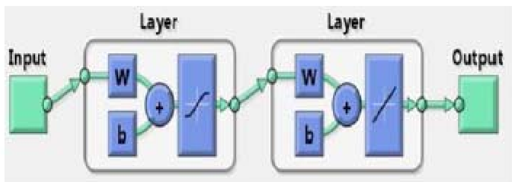

Fig 4. ANN Training Data

In the hidden layer there is a sum of the multiplication of the input value and the weights value. The output of the hidden layer will be calculated using the activation function to produce the desired output value. In ANN there is a learning process, which is to determine the weights value between neurons. In the learning process, training will depend on two inputs and one output. The training system is setting the weights value between input and output that will be used to train the network so that the output of the ANN matches the desired target. After training, the weights value will be obtained, while before the training the value of the weights is chosen randomly [12]. When the pattern is obtained, the pattern will be sent to process input data so that it can produce output and be matched with the learning pattern. If there is an error between the resulting output and the desired output, the ANN will be run for second time until the error obtained is within the tolerance limit [13].

C. Electrical Bus

The use of electric buses can support efforts to reduce air pollution due to the use of fossil fuels in transportation. Urban air quality is increasingly attracting public attention and several international cities are planning to ban fossil fuel vehicles from being used in cities. Even diesel engines emit harmful substances such as nitrogen oxides (NOx) and other harmful particles. Electric buses that do not require fossil fuels will not cause air pollution so they can make the environment cleaner and healthier. This electric bus technology is expected to improve several aspects, i.e., reducing harmful emissions, increasing vehicle efficiency, increasing performance, reducing fuel consumption, reducing noise, and potentially cost-effective maintenance.

The important thing of electric vehicle is a combination of an electric motor, controller and battery. The battery sends power to the controller and then to the motor. The accelerator knob provides a signal to the controller to estimate the power to be delivered under certain load conditions. The controller can provide zero power when the vehicle is stationary, full power when the accelerator knob is raised to full speed, or a power level in between [14]. In general, electric motors used in electric vehicles must be able to operate for a long time, have a constant speed, slightly variable load, and so on. For electric vehicle applications, the motor needs to be started, stopped frequently, accelerated and decelerated periodically which cannot be compared with industrial electric motors [14].

For electric motors to be suitable for use in electric vehicles, several key conditions must be met to operate at good performance and efficiency. Motors for electric vehicles must have high torque to start operating and go through grades, high power density for acceleration and acceleration, capacity to withstand loads for certain time intervals, reliable, efficient, and affordable cost. The speed torque characteristics of a motor determine whether it is suitable for use in electric vehicles. Figure 5 shows the speed-torque characteristics of the desired electric vehicle motor [15].

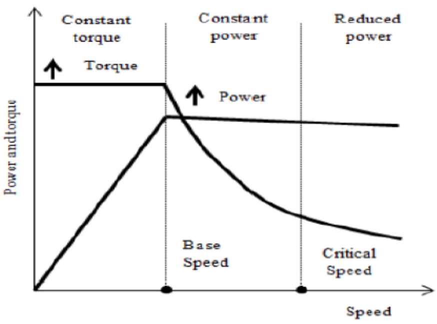

Fig 5. Motor Speed-torque characteristic for electric vehicles

Design of Simulation System

Hall effect sensors on BLDC motors are used to detect the position of rotor inside the BLDC motor. Each Hall effect sensor will provide information in the form of a High or Low signal according to polarity of rotor magnetic poles. The signal generated by Hall effect sensor will be forwarded to commutation logic and then inverter to determine which switch will be powered by voltage source. The voltage that enters inverter is the reference voltage generated by ANN.

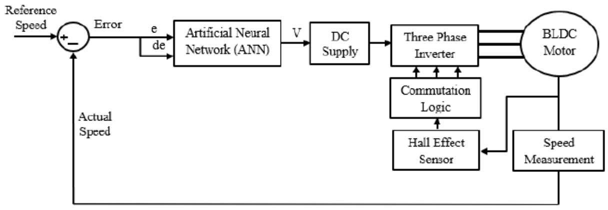

Fig 6. Block Diagram Speed Control System

A. Modeling Learning ANN

BLDC motor speed controller is helped by Artificial Neural Network (ANN) method to determine the BLDC motor input voltage reference so that the resulting speed can match the reference speed. In ANN there is a learning process that function is to determine the weighting value between neurons which will form a pattern for processing information data, so the ANN will be able to produce desired output according to input information provided. This study uses 6330 data for ANN learning, more data that learned, ANN will produce a more accurate pattern for processing an information data.

Training function is one of stages in learning Artificial Neural Network. At training stage, each weight and bias on each neuron will be updated continuously until the resulting output is in line with expectations. The training function used in this research is Levenberg Marquardt. Levenberg Marquardt can be used for simple problems, can learn quickly, and has a lot of memory. Figure 7 and Figure 8 show that the author choose the Levenberd Marquardt as training function and use 10 hidden layer in the nftool toolbox.

Hidden layer is a layer that used to pass from input to output. The more hidden layers the learning process will take longer, but the MSE will be better. However, using many hidden layers will overfitting the ANN. In this study using 10 hidden layers in accordance with the recommendations of MATLAB. If you set too much on hidden layer it can caused overfitting

B. Specification Motor BLDC

The BLDC motor specification using a reference from MATLAB by changing some parameters. In this research, the specifications that are replaced from BLDC motors are stator resistance and stator inductance. For other parameters use the specifications that provided by the BLDC motor block diagram in Simulink.

Table 1. Specification of Motor BLDC

Parameter	Value
Stator Phase Resistance Rs (ohm)	0.1116
Stator Phase Inductance Ls (H)	0.001224
Flux Linkage (V.s)	0.043175
Voltage Constant (V. peak L-L/krpm)	36.1702
Torque Constant (N.m/Apeak)	0.3454
Back EMF flat area (degrees)	120
Pole pairs	4

C. Modelling Speed Control System

The simulation model of BLDC motor speed controller using Simulink MATLAB software can be seen in Figure 9. BLDC motor speed controller is helped by the Artificial Neural Network (ANN) method to determine the BLDC motor input voltage reference so the resulting speed can match the reference speed. When simulation is run, the rpm value of the motor will be obtained. The rpm value of motor will be compared with reference speed. If there is an error, then this error will go to the ANN.

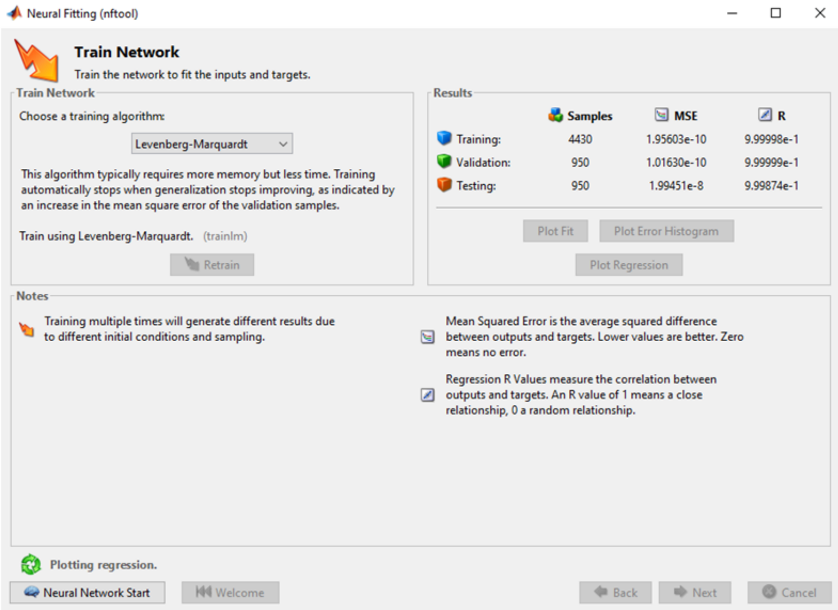

Fig 7. Determine the Training Function

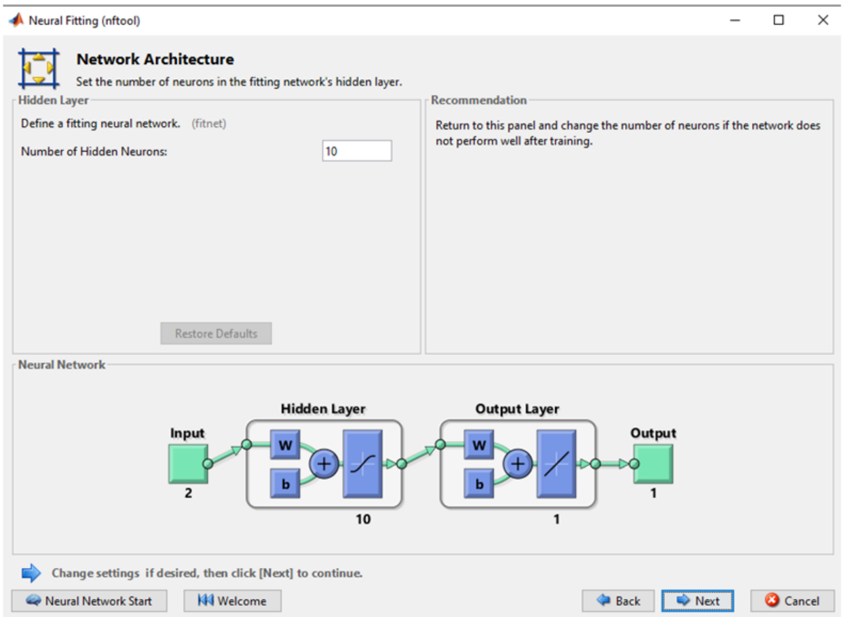

Fig 8. Determine the Hidden Layer

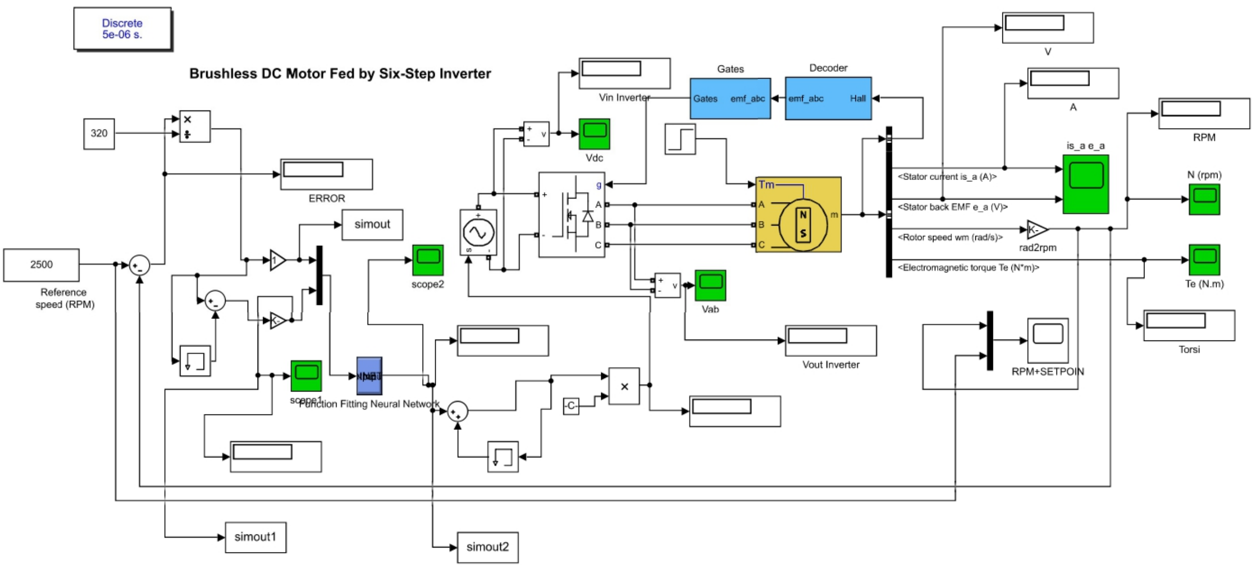

Fig 9. Modelling System in Simulink

The ANN that has been learning will be equipped with weight and bias values between neurons and an activation function that will process input data so the ANN will produce an output in form of a voltage reference that is sent to a 3-phase inverter. The inverter will convert the DC voltage into AC voltage by turning on the switch in the order received from the Hall Effect sensor signal. The BLDC motor will get an AC voltage so it can produce a rotating field and BLDC motor rotates. The speed obtained on this BLDC motor will be returned and compared with reference speed. If there is an error, this error will re-enter ANN and difference between error generated earlier and now will be a delta error and become input of ANN so the ANN will work with two inputs. And speed control process will repeat until resulting error is very minimal.

Simulation Results And Data Analysis

A. ANN Learning Results

The learning process used in this study uses a feed forward neural network with two inputs and one output. The results of learning neural network, i.e., epoch results of learning ANN are 19 iterations. Epoch is a measure of how many times train is used to update the weights between neurons. One epoch is when all the learning data goes through one forward and backward process and passes through all the neural network nodes once. For learning results obtained epoch 19, so ANN learning process goes through the forward and backward 19 times and passes through all the neural network nodes 19 times.

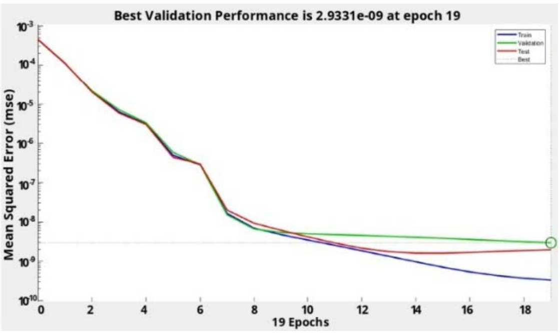

Fig 10. Plot Performance ANN

In performance plot, Figure 10 shows that the training network stops at epoch 19 with MSE showing 2.9331e-09 and validation and test lines are close to best dotted line. So the neural network learning process that has been carried out has the Best Validation Performance, which is 2.9331e-09 at epoch 19. The MSE on learning neural network results shows the performance error of learning that has been done, the smaller MSE, the better learning neural network results will be and resulting error is getting smaller.

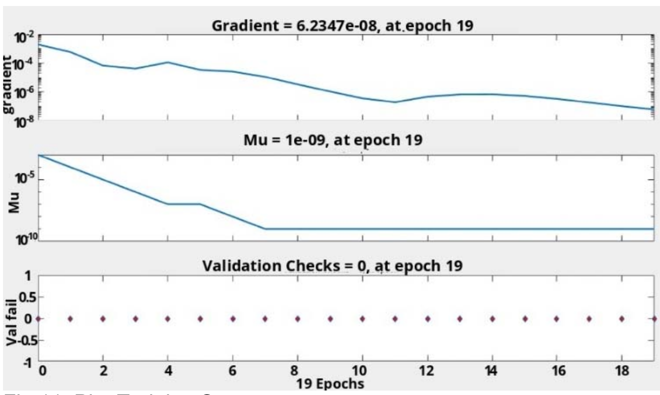

Fig 11. Plot Training State

From plot training state, Figure 11. shows that with gradient 6.2347e-08, learning has reached the lower minimum of intended function, which is close to zero. From Figure 11. it can be seen that gradient value continues to decrease with increasing number of epochs. Mu, the minimum damping factor in Levenberg-Marquardt algorithm used by the network is 0.001 and the threshold for Mu is 1e+10. The actual value of Mu is 1e-09. Validation checks, is generalization ability to check network standards. The value of validation checks shows zero, meaning that error continues to decrease during training process. In the plot training state in Figure 11. retraining is no longer needed, if the training continues, it can caused over learning.

In plot histogram error, it can be seen that in the middle of the plot there is a bin with an error of -5.9e-05. The height of each bin or bar is to show the amount of test data or called an instance. The bin height for training dataset is around 3500, bin height for validation dataset and test dataset is between 3500 and 5000. It means that 3500 data samples are used for training dataset and the rest of other data samples have errors that lie in the range of -5.9e-05. The sign of zero error will indicate the direction of the bias. The X axis defines the error between the target and the output. It can be seen that zero error is located close to bin which has a negative error. Thus, most of the target values are greater than the output.

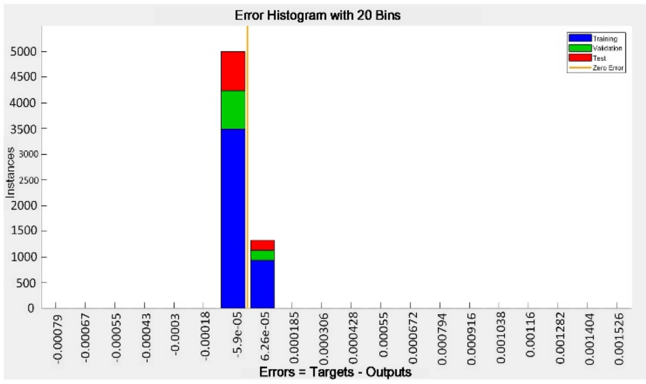

Fig 12. Plot Error Histogram

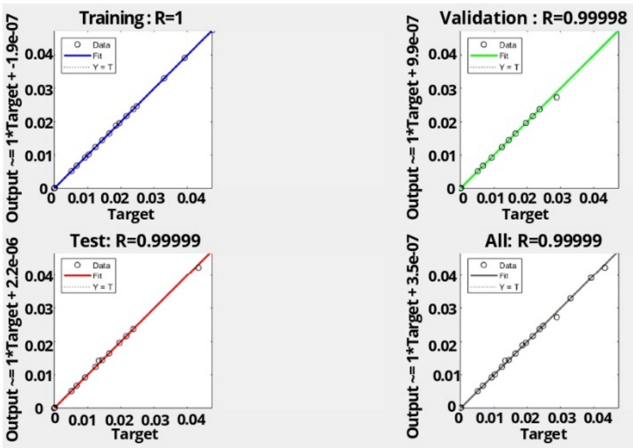

Fig 13. Plot Regression ANN

The value of R is an indication of relationship between output and target. If R=1, then there is an exact linear relationship between output and target. If R is close to zero then there is no linear relationship between output and target. In results of regression plot above, the training data shows a good match where the value of R=1. For the validation and test results, it also shows a large R value and is close to the value 1. So, by obtaining an R = 1 value and an R value close to 1, there is a linear relationship between the output and the target. So the ANN learning can be said to work well.

B. No-load BLDC Motor Simulation

In no-load BLDC motor test, the aim is to determine the characteristics of BLDC motor when it is not loaded. At reference 2500 rpm, the result is the time required for motor to reach steady state (settling time) is 0.621 s with a rise time of 0.219 s. Testing of BLDC motors without load shows a good response where the speed of BLDC motor can reach steady state and does not have overshoot. The resulting torque response is when starting the motor, torque generated is quite large because it is used to drive motor and slowly the torque will drop to minimum value where the motor speed has reached a steady state value.

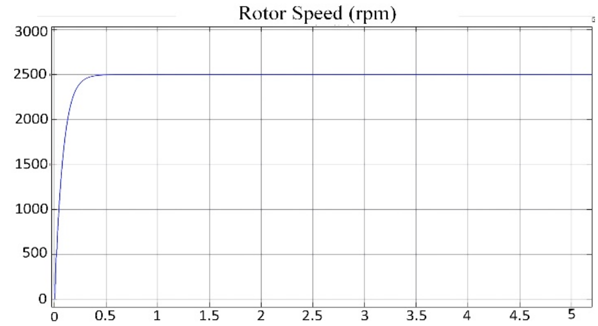

Fig 14. No-load Speed Response at Set Point 2500rpm

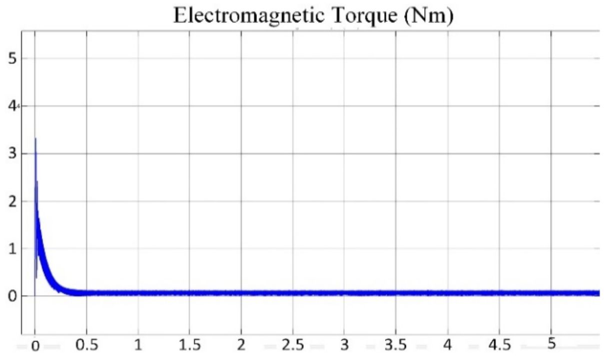

Fig 15. No-load Torque Response at Set Point 2500rpm

C. Load BLDC Motor Simulation

The BLDC motor simulation process is done using 6 references with a load torque of 30 N.m.

Table 2. Loaded BLDC Motor Test Results

Set Point (rpm)	Actual Speed (rpm)	Tr (ms)	Ts (s)	Mp (%)	Voltage (V)	Current (A)
2500	2480	290.6	1.35	1.97	42.55	67.94
3000	2976	433.2	1.39	0.63	59.54	72.59
3200	3174	424.8	1.55	0.57	63.54	73.15
3400	3372	440.9	1.41	0.96	67.49	73.46
3600	3571	445	1.49	0.96	71.49	73.85
3800	3769	447.72	1.62	0.688	75.39	74.3
4000	3967	455	1.6	0.447	79.35	74.56

Where tr is rise time (ms), ts is settling time (s), and Mp is overshoot (%). For rise time, it can be seen that the higher the speed of BLDC motor, the higher the rise time. And this also applies to settling time, where the higher the motor speed, the longer time required for steady state will be. Voltage and current are directly proportional to the speed of BLDC motor, the higher the motor speed, the higher the voltage and current. In Table 2. it can be seen the results of the torque test on BLDC motor. The torque response of the BLDC motor speed control system using ANN causes a large torque ripple in each test. The average ripple torque obtained from the test is more than 30%. For the error obtained between actual speed and speed reference, the higher the motor speed reference, the higher the error generated. The average error between actual speed and speed reference is 0.81%.

Table 3. Torque Test Results and Loaded BLDC Motor Error

Set Point (rpm)	Actual Speed (rpm)	Error (%)	Torsi (N.m)	Ripple Torsi (%)	Daya (kw)
2500	2480	0.8	30.2	38.2	74.9
3000	2976	0.8	30.21	30.64	89.9
3200	3174	0.81	30.22	31.76	95.92
3400	3372	0.82	30.23	34.7	101.93
3600	3571	0.806	30.24	35	107.99
3800	3769	0.82	30.24	34.3	113.97
4000	3967	0.825	30.25	32.72	120

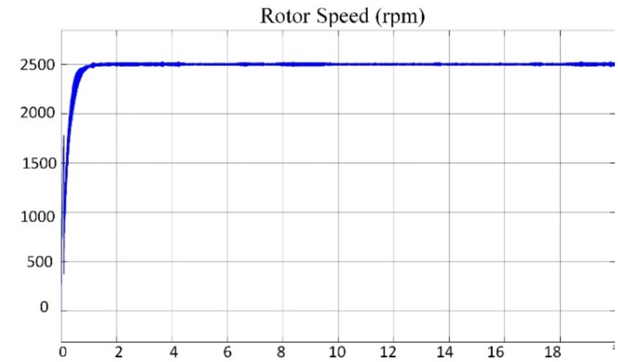

Fig 16. Loaded Speed Response at Set Point 2500rpm

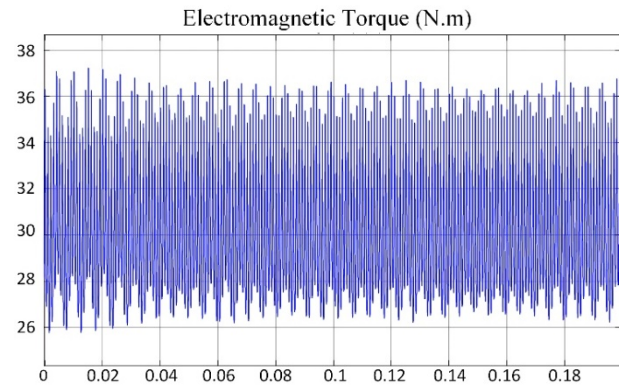

Fig 17. Loaded Torque Response at Set Point 2500rpm

At the reference speed 2500 rpm, it produces an actual speed 2480 rpm and produces a speed response that has a rise time 290.6 ms with an overshoot 1.97% and can reach steady state in 1.35 s. While the torque response at the reference speed 2500 rpm has a torque ripple of 38.2%.

D. BLDC Motor Simulation with Load Variation

In this test, it is done by giving a sudden load change. The load will suddenly be increased from 0 N.m to 45 N.m at t=5 s. And then the load is suddenly decreased from 45 N.m to 15 N.m at t=9 s.

When motor is starting, rotor will rotate until it reaches the reference speed. When starting, torque will increase for a moment and finally drop to a minimum value (0 N.m) along with the motor speed that has reached steady state or reaches reference value. At time of starting motor without load, time required to reach steady state value is 0.528 s with a rise time 112.91 ms and does not have overshoot. When given a sudden load at t=5 s of 45 N.m, the motor experiences an overshoot -79.84%, and slowly motor speed increases towards reference value with a settling time 671.785 ms. The resulting torque response is torque increases according to given load and there is a torque ripple. When load is reduced to 15 N.m at t=9s, the motor experiences an overshoot of 28.9% and can reach a steady state value with a time 1.0175 s. When load is lowered, the resulting torque response also decreases according to loading torque.

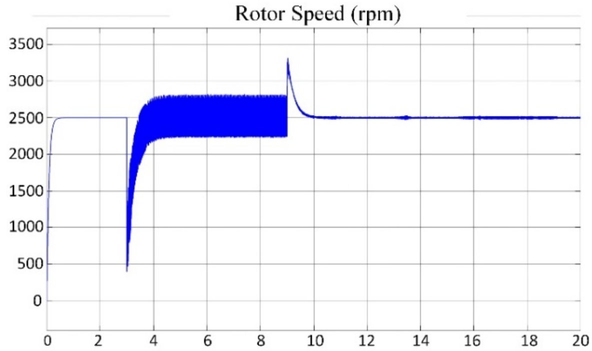

Fig 18. Speed Response at Set Point 2500rpm with Load Variation

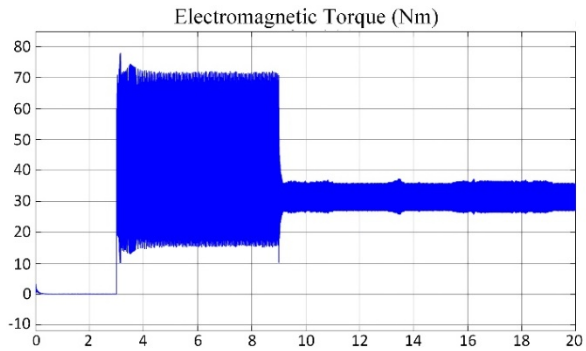

Fig 19. Torque Response at Set Point 2500rpm with Load Variation

In simulation of BLDC motor speed controller, the resulting torque response has a torque ripple in each test. The ideal BLDC motor has a trapezoidal backemf signal. Zero torque ripple will be generated for trapezoidal wave signal when the motor is fed by rectangular current. For example, when backemf is in form of a trapezoid with a flat top width of 120 electrical angles, at the same time the phasspeee current waveform must be rectangular with a width of 120 electrical angles. However, due to the non-uniformity of magnetic materials and design tradeoffs, it is difficult to produce a trapezoidal waveform. Therefore a torque ripple appears even though the square current is fed in conventional control. In addition, because motor winding is inductive, the current controller often fails to produce required waveform, so the backemf or current waveform is not as in ideal conditions. Torque ripples can be suppressed by various construction changes such as tilting the stator slots or permanent magnet segments, but this solution leads to a more expensive physical manufacture of motor. In simulation, to reduce torque ripple can be done by analyzing and identifying the cause of ripple in the system, and using a closed loop for controlling of the armature current or the torque to regulate and reduce torque ripple in the system.

Figure 20. is one of the results of current and backemf waveforms in BLDC motor testing. It can be seen that the backemf waveform is trapezoidal while the current waveform is not rectangular. This may be one of the reasons for torsion ripple in every BLDC motor test. Torque ripples can cause unwanted noise, vibration in speed applications and can cause inaccuracies in control.

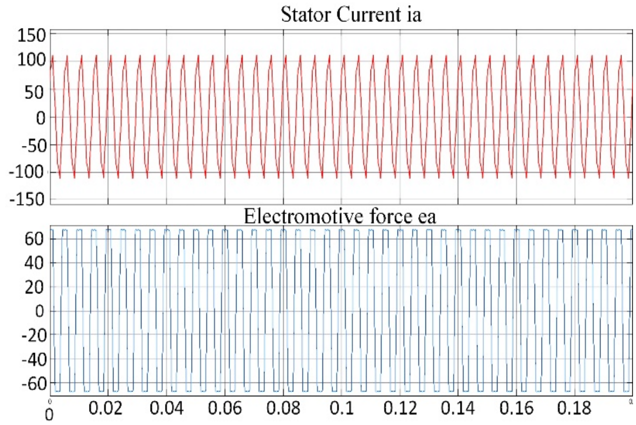

Fig 20. Current and Backemf Waveform

Simulation results of speed control using ANN shows that the time required for motor to reach steady state value is very fast. Compared to Fuzzy Logic, ANN gives a better response because using Fuzzy Logic takes a long time because of the complex fuzzification and defuzzification process. Using ANN also make it easy to design a controller as long as it has enough data for learning. In designing ANN as a controller it only requires sufficient data for learning, then determines the training algorithm to be used, determine hidden layer between neurons, after that the ANN will process the data itself and produce a mapping relationship between input and output.

Conclusion

Here are some conclusions from the research that has been done :

1) The results of ANN learning process from this study have an MSE 2.933e-9 where the smaller the MSE, the more accurate the output produced by ANN.
2) The results of regression plot show the value of R = 0.9999 where the closer the R value is to 1, there is an exact linear relationship between output and target.
3) No-load motor speed control using the ANN method can work well, where the motor speed can reach the reference value correctly and do not have overshoot.
4) The additional load on motor speed control system results in an average error between speed reference and actual speed is 0.81% and there is a torque ripple from each system test, the resulting torque ripple is more than 30% in each test.
5) Testing the motor under varying load conditions has been analyzed based on overshoot, rise time, and settling time for each load change. The results obtained indicate that variations in speed and torque can follow load variations well.

Acknowledgements
The Author thanks to Institut Teknologi Sepuluh nopember and funding source Ristek Brin Skema PRN_BOPTN which support to finish this paper

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