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STUDY OF BRUSHLESS MOTOR CONTROL METHODS BASED ON AI ALGORITHMS

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Abstract. The paper is devoted to the study of controllers based on artificial intelligence: a fuzzy logic controller (FLC), an artificial neural network (ANN) based on a multilayer perceptron, and an adaptive neuro-fuzzy inference system (ANFIS). Traditional PID controllers demonstrate limited efficiency in controlling brushless motors under conditions of variable loads and disturbances due to the inability to adapt to the nonlinearities of the systems. A comprehensive DC motor model was developed in the MATLAB/Simulink environment and tested under dynamic conditions (acceleration, deceleration, variable load). Speed/torque overshoot metrics are used, as well as the time of setting. The results show that ANFIS provides excellent accuracy (overspeed is 45% lower compared to PID), but suffers from slower reactions. ANN provides an optimal balance by reducing overspeed by 7% and regulation time by 35% compared to PID, while maintaining real-time applicability. The FLC has excellent transient performance, but exhibits torque fluctuations. The study confirms that controllers with artificial intelligence significantly increase adaptability to disturbances and non-linearities, and ANNs are recommended for real-time systems (robotics, drones), and ANFIS for precision applications. The results provide engineers with some recommendations on the choice of control algorithms for modern electric drives that require resistance to disturbances and energy efficiency.

Keywords: brushless motors; neural networks; fuzzy logic; hybrid systems; intelligent controllers; energy harvesting devices based on multiferroic materials

1. Introduction

The paper focuses on the application of artificial intelligence techniques, such as neural networks and fuzzy logic, to control brushless direct current (BLDC) motors. These techniques are expected to significantly improve the performance of these motors compared to traditional proportional-integral-derivative (PID) controllers.

In the era of rapidly developing information technologies, artificial intelligence (AI) is penetrating into a wide variety of industries, becoming a new stage of development in technology. One of these promising areas is engine control, something that no moving device can do without, whether it's cars, airplanes, industrial installations, or energy systems.

The introduction of algorithms opens up new opportunities. The use of artificial intelligence algorithms (neural networks, fuzzy logic, hybrid systems) to control BLDC engines allows for the implementation of an intelligent speed controller (AI-ESC) capable of analyzing data in real time, adapting to real-world operating conditions, predicting failures, and significantly improving the key performance of the controlled device.

The authors of the paper [1] conclude that PID controller is a simple controller with a simple tuning method but with a moderate response and performance. Fuzzy controller is more complicated controller but with a good and more stable performance. Euro fuzzy controller is very complicated controller but with a very good performance.

In study [2] authors have compared the use of an intelligence controller on the BLDC motor using data extraction from one of the intelligence controllers. The test was carried out by two scenarios, and analyzing the results of the system response was carried out by graph and some statistical parameters such as MAE, IAE, ITAE, and ISE. We found in scenario 1, ANN has a better performance compared to other controllers with the MAE, IAE, ITAE, and ISE value of 31.3003; 105.6280; 208.0630; and 5,7289 e4, respectively.

In paper [3] authors presents an ANFIS controller for speed control of BLDC motor along with comparisons with other controllers, PID and Fuzzy controllers. ANFIS controller showed the best results.

The performance analysis of BLDC motor under transient and steady-state with the two different controllers such as PI and ANFIS is studied in work [4] by using the MATLAB/Simulink 2021a version. From the results, it is clear that the ANFIS controller outperforms PI at all speeds and under various operating conditions.

Classical systems work based on precise mathematical models and linear algorithms. Such systems require fine tuning, are unable to account for external reimbursements, predict failures, or adapt to changes without human intervention.

The use of artificial intelligence algorithms (in particular, neural networks, fuzzy logic and their hybrids) to control brushless DC motors (BLDC) makes it possible to dynamically adjust the parameters of the brushless motor control system to changing environmental conditions more efficiently than the PID control method.

The article provides a comparative analysis of the effectiveness of artificial intelligence algorithms (neural networks, fuzzy logic, neuro-fuzzy systems) for controlling the speed of a brushless DC motor (BLDC) in order to confirm their advantages over classical approaches.

2. Studied ai algorithms

The following algorithms were chosen for study:

Fuzzy Logic Controller;

Neural network based on a multilayer perceptron (ANN Controller);

Neuro-fuzzy model (ANFIS Controller).

These algorithms were chosen because they are highly adaptable and easy to implement.

FLC uses fuzzy rules to model the knowledge of specialists, which provides increased stability and is useful in managing systems with uncertainty and nonlinearities. ANFIS has the ability to learn from data, which makes it possible to adapt the control system to changing operating conditions and engine parameters, which was presented in [5]. ANFIS combines the advantages of fuzzy logic and neural networks, providing automatic adjustment of rules and parameters, which increases the accuracy and stability of control.

2.1. Tools and modeling

Matlab/Simulink was chosen as the tools, which allows you to simulate the operation of complex devices. In [6], a mathematical model of a brushless DC motor with specified parameters was constructed using Matlab/Simulink, and the theoretical foundations of the mathematical model were confirmed in the simulation results.

To conduct research on the control and speed control system, it was necessary to simulate the operation of the BLDC and ESC controller in Simulink. The purpose of the simulation is to develop and test effective control algorithms before implementing them in real devices.

The SunnySky V4014 330KV BLDC was selected for the experiments.

The general scheme of the model consists of the following parts: power supply, the inverter, BLDC, Hall sensors, switching logic, feedback, regulating controller, APWM generator.

2.2. Development and application of fuzzy controller (FLC)

To conduct the study, a BLDC model with a fuzzy controller control was built in Simulink. The block diagram of BLDC with fuzzy controller is shown in Figure 1.

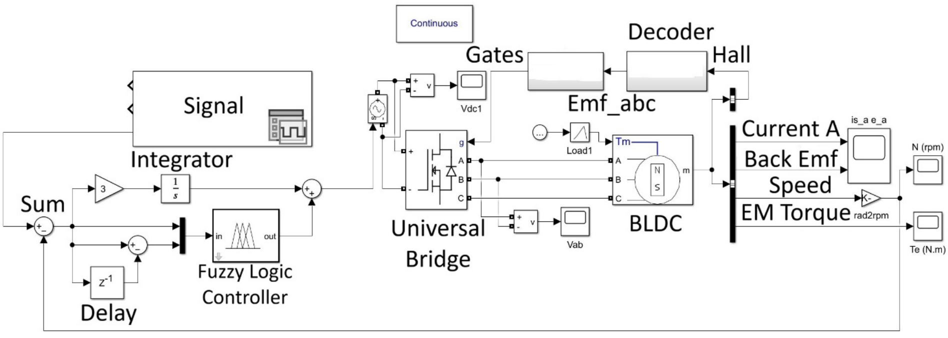


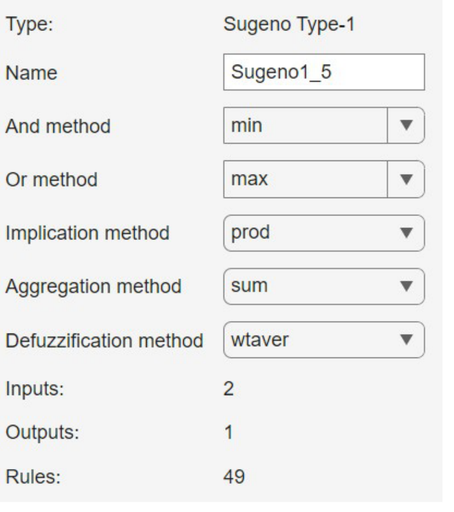
Figure 1. BLDC with fuzzy controller

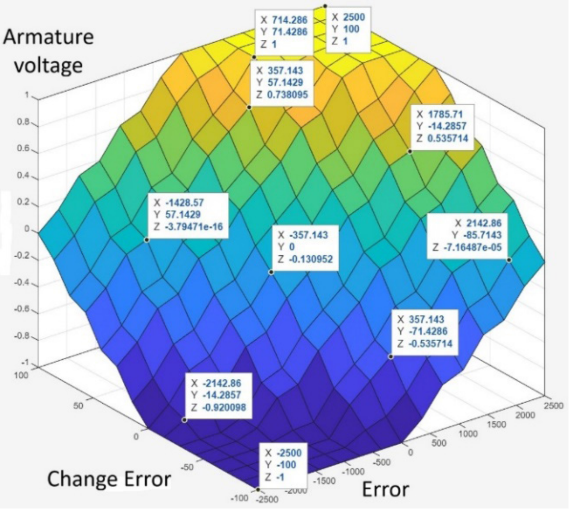
The following variables are used as input variables:
speed error error e(t) = w_ref – w_fb;
error change delta_error de/dt or Δe.
The output variable is the control signal U(t).
Sugeno metod was chosen as the type of fuzzy inference of FLC.
7 membership functions were defined for the input variables error, and change_ error. The variables have the following range of input data: error [-2500 2500]; change_error [-100 100]; armature_voltage [-1 1].
For 7 membership functions and 2 input variables, a 7x7 matrix of fuzzy rules is obtained. In [7], 2 input variables and a 7x7 matrix were also used to implement the fuzzy controller. The matrix of fuzzy rules is presented in Table 1.

Table 1. The matrix of fuzzy rules

E/CE	NB	NM	NS	Z	PS	PM	PB
NB	NB	NB	NB	NB	NM	NS	Z
NM	NB	NB	NB	NM	NS	Z	PS
NS	NB	NB	NM	NS	Z	PS	PM
Z	NB	NM	NS	Z	PS	PM	PB
PS	NM	NS	Z	PS	PM	PB	PB
PM	NM	Z	PS	PM	PB	PB	PB
PB	Z	PS	PM	PB	PB	PB	PB

By defining the parameters of the fuzzy system And, Or, Implication, Aggregation, Defuzzification, Inputs, Outputs, Rules, as well as membership functions, a fuzzy system was obtained. Fuzzy system parameters, control surface and the result of the regulator operation is shown in Figure 2.


Type: Sugeno Type-1
Name Sugeno1_5
And method min
Or method max
Implication method prod
Aggregation method sum
Defuzzification method wtaver
Inputs: 2
Outputs: 1
Rules: 49


Armature voltage
Change Error
Error
X 714.286 Y 71.4286 Z 1
X 2500 Y 100 Z 1
X 357.143 Y 57.1429 Z 0.738095
X 1785.71 Y -14.2857 Z 0.535714
X -1428.57 Y 57.1429 Z -3.79471e-16
X -357.143 Y 0 Z -0.130952
X 2142.86 Y -85.7143 Z -7.16487e-05
X 357.143 Y -71.4286 Z -0.535714
X -2142.86 Y -14.2857 Z -0.920098
X -2500 Y -100 Z -1

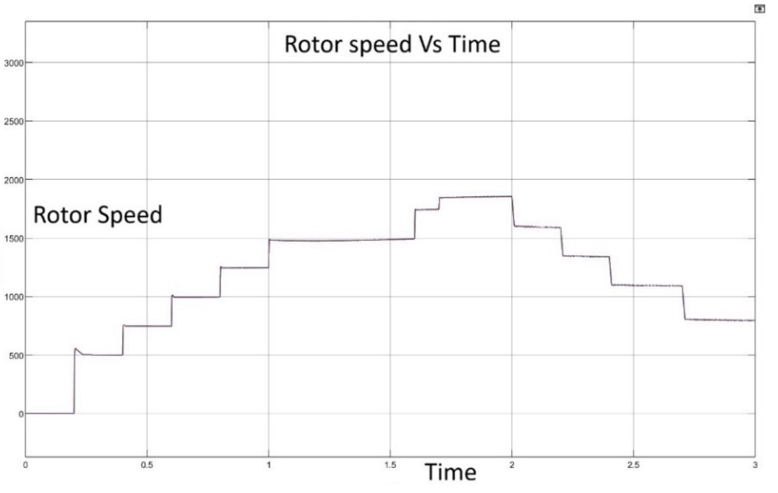


Figure 2. Fuzzy system parameters, control surface
and the result of the regulator operation

As a result of FLC simulation in the Simulink environment, the following results were obtained. Metrics of the FLC controller operation: Speeding is 0.0743, Setting time is 0.0654, Excess torque is 0.383, Torque setting time is 0.08.

2.3. Development and application of a neural network controller (ANN)

To conduct the study, a BLDC model was built with a controlling neural controller in Simulink. Feedback BLDC model with ANN controller is shown in Figure 3.

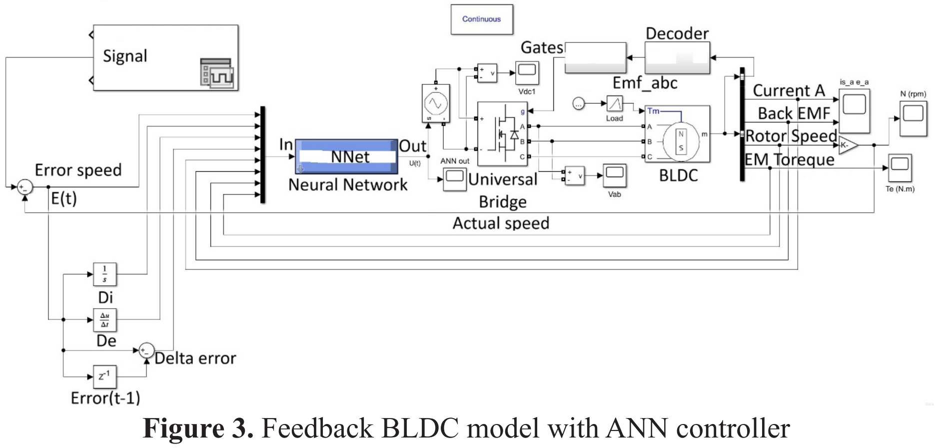


Figure 3. Feedback BLDC model with ANN controller

The neural network architecture is a three – layer multilayer perceptron (MLP) with 8 input parameters. The work [8] describes in detail the operation of the layers, the architecture, and the parameter estimation algorithm itself.

MSE = 0.000747. On average, the controller makes very few mistakes.

RMSE = 0.027339. The average speed prediction error is 0.0273.

MAE = 0.015593. On average, the speed prediction deviates from the true one by only 0.0156 units. This confirms the conclusions of the MSE and RMSE on the high accuracy of the controller.

MAPE = 127.711997%. The presence of speed values very close to zero (or equal to zero). Even a small absolute error (for example, 0.0156) with a true value will give a huge percentage of error (156% in this example). As a result, MAPE becomes an unstable and uninformative metric in such situations. This result may be affected by:

The presence of very low (or zero) data;

The algorithm of the controller operation at low speeds;

R^2 = 0.968705, which means that the ANN model is exceptionally good at describing patterns in the data related to speed control. The controller demonstrates excellent speed prediction and control accuracy, which is confirmed by very low MSE, RMSE, MAE and high R^2.

The key problem was identified by the MAPE metric. It is highly likely that the controller is incorrectly configured to operate at very low speeds close to zero. This is a typical problem for engine management and for the MAPE metric.

To use the obtained ANN controller model in Simulink, a neural block was generated with the parameters that were obtained during training. Save the trained network and normalization parameters (if used) in a format that Simulink can download. Metrics of the ANN controller operation: Speeding is 0.0691, Setting time is 0.0524, Excess torque is 0.289, Torque setting time is 0.0556.

2.4. Development and application of the neuro-fuzzy controller (ANFIS)

To implement the hybrid ANFIS controller, it was necessary to build a fuzzy inference system (FIS) and train its neural part. The ANFIS model in Simulink is similar to FLC. Feedback BLDC model with ANFIS controller is shown in Figure 4.

Error and error_change were defined as input data because this solution gives results similar to the PID controller, but with the potential for better adaptability.

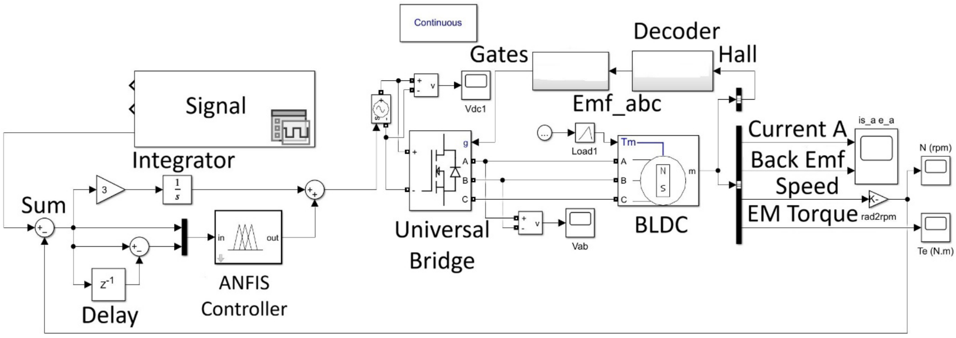


Figure 4. Feedback BLDC model with ANFIS controller

Error and error change were defined as input data because this solution gives results similar to the PID controller, but with the potential for better adaptability.

MSE = 0.0134. small value.

RMSE = 0.1158. The standard deviation of the prediction error. It has very little value, because real BDTPS operate at speeds of several thousand revolutions per minute.

MAY = 0.0900. The average speed forecast differs from the actual value.

NRMSE = 8.56%. For electric motor control systems, a value of <10% is considered a good result.

R^2 = 0.4387. Explains 43.87% of the speed variation, which is a low value.

The ANFIS controller successfully copes with the basic tasks of BLDC speed control, but requires refinement to work in extreme conditions and under variable loads.

The trained model is loaded and runs in Simulink like a regular FIS model, i.e. by selecting a fuzzy model in the FLC parameters. ANFIS regulator performance metrics: Speeding is 0.045, Setting time is 0.3304, Excess torque is 0.0474, Torque setting time is 0.679.

The authors of [9] conclude that the ANFIS controller is an excellent choice for high-performance BLDC motor speed control systems and is suitable for real-world applications.

In the study [10], the authors combined ANFIS with a genetic Algorithm (GA), which resulted in higher efficiency and automatic optimization.

2.5. Comparative analysis of management methods

ANFIS is the leader in accuracy (minimum overshoot), but it is not applicable in systems with performance requirements. ANN is the best compromise option: it improves accuracy and response speed at the same time. Fuzzy is optimal for tasks where reaction time is critical, but fluctuations are acceptable. PID is inferior in all respects, except for ease of implementation.

Neural network methods (ANN/ANFIS) are superior to classical approaches in accuracy, but ANFIS sacrifices speed. ANN is the most balanced solution for BLDC control, combining improved accuracy with better dynamics. ANN or Fuzzy are best suited for real-time systems (robotics, engines). For high-precision systems (laboratory equipment) - ANFIS. The PID is relevant only with limited resources or no dynamic requirements. Controller operation analysis is shown in Table 3.

Table 2. Comparative analysis of management methods

Parameter	PID	Fuzzy	ANN	ANFIS
Speeding	0.0743	0.0743	0.0691	0.045
Setting time	0.081	0.0654	0.0524	0.3304
Excess torque	0.383	0.383	0.289	0.0474
Torque setting time	0.1	0.08	0.0556	0.679

Conclusion

Hybrid approaches combining the advantages of neural networks and fuzzy logic, such as ANFIS or ANN, can provide maximum efficiency for modern BLDC control systems operating under conditions of variable loads and requiring high adaptability. Our experimental data confirm that the transition to intelligent regulators can significantly improve the quality of control. In addition, this technology makes it possible to implement algorithms for efficient energy harvesting in magnetoelectric generators.

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