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OPTIMIZING BLDC MOTOR PERFORMANCE THROUGH NARMA-L2 MODEL-BASED CONTROL STRATEGY

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ABSTRACT
This paper introduces a novel approach to controlling Brushless DC (BLDC) motors using Artificial Intelligence (AI), specifically through the Nonlinear Auto Regressive Moving Average with exogenous inputs (NARMA-L2) model. By utilizing MATLAB simulations, this method is compared to the traditional Proportional-Integral-Derivative (PID) controller, which was optimized using an optimization technique in prior research. The results demonstrate that the NARMA-L2 model provides better adaptability and efficiency, addressing the limitations of conventional control methods. The proposed AI-based approach improves speed regulation, torque response, and overall system stability, making it a more effective alternative. Additionally, this study highlights the potential of AI in solving complex control challenges in electro-mechanical systems, paving the way for further research and real-world applications in various industries.

Keywords: BLDC, PID,NARMA-L2

1. Introduction
In recent years, Brushless DC (BLDC) motors have gained widespread attention across various industries due to their advantages over traditional brushed DC motors and induction motors. These advantages include higher efficiency, greater reliability, and lower maintenance requirements, making BLDC motors well-suited for applications in automotive systems, robotics, aerospace, and industrial automation. To fully utilize their potential and ensure optimal performance in different operating conditions, effective control strategies are essential.
Traditional control methods for BLDC motors primarily rely on Proportional-Integral-Derivative (PID) controllers, which are widely used due to their simplicity and effectiveness. However, PID controllers have certain limitations, particularly when dealing with non linearities, uncertainties, and external disturbances in real-world systems. Tuning a PID controller to achieve optimal performance can be a complex and time-consuming process, requiring significant empirical knowledge and multiple adjustments. Additionally, PID controllers may struggle to maintain stable performance under changing operating conditions or unexpected disturbances.
To address these challenges, researchers have explored advanced control techniques, including Artificial Intelligence (AI) and machine learning-based approaches. These methods offer improved adaptability, robustness, and flexibility for handling complex control tasks compared to traditional techniques. Among AI-driven control strategies, the Nonlinear Auto Regressive Moving Average with exogenous inputs (NARMA-L2) model has gained attention for its ability to handle nonlinear dynamics and effectively control dynamic systems.
This study proposes the application of the NARMA-L2 model for BLDC motor control and evaluates its effectiveness through MATLAB simulations. The NARMA-L2 model, built on a nonlinear dynamic neural network architecture, leverages historical system data and external inputs to predict system behavior and generate precise control signals. By incorporating AI techniques, this approach aims to improve speed regulation, torque response, and overall system stability in BLDC motor applications.
The motivation behind this research is to overcome the limitations of conventional control strategies and explore innovative solutions to enhance BLDC motor performance. While previous studies have

demonstrated the potential of AI-based control methods in various engineering domains, including motor control, process control, and robotics, there remains a gap in research regarding the specific application of the NARMA-L2 model for BLDC motor control and its comparative performance against PID controllers. This study seeks to bridge that gap and provide insights into the advantages of AI-driven control strategies in electro-mechanical systems.

This study aims to bridge the existing research gap by conducting a detailed evaluation of the proposed NARMA-L2-based control strategy for BLDC motors. The performance of the NARMA-L2 model will be compared with that of a PID controller, which has been optimized using established tuning techniques and is commonly used in prior studies. Through MATLAB simulations, the study will assess key performance metrics, including speed regulation, torque response, transient behavior, and robustness to disturbances. This evaluation will help determine the effectiveness of the NARMA-L2 model in improving BLDC motor control and addressing the limitations of traditional PID-based methods.

Overall, this research contributes to the advancement of control techniques for BLDC motors by introducing an AI-based approach that offers improved performance and robustness compared to conventional methods. The findings of this study have implications for the design and implementation of BLDC motor control systems in real-world applications, potentially leading to enhanced efficiency, reliability, and adaptability in various industrial and commercial settings.

2. Literature

Over the past five years, significant advancements have been made in BLDC motor control, with researchers exploring various strategies to enhance performance and efficiency. This literature review provides an overview of recent studies related to BLDC motor control, highlighting key trends and innovations.

One major development in this field is the increasing adoption of Artificial Intelligence (AI) and machine learning techniques to overcome the limitations of conventional control methods. For example, Zhang et al. (2021) introduced a deep reinforcement learning-based control strategy that demonstrated superior speed regulation and robustness compared to PID controllers. Similarly, Li et al. (2020) proposed a neural network-based adaptive control approach, which improved speed tracking accuracy and disturbance rejection.

Beyond AI-based methods, researchers have explored advanced control algorithms specifically designed for BLDC motors. Huang et al. (2023) developed a Model Predictive Control (MPC) scheme that significantly reduced torque ripple and enhanced dynamic response. Sharma et al. (2022) introduced a fuzzy logic-based control strategy, which provided better performance under varying operating conditions and load disturbances.

Optimization of control parameters has also been a focus in recent studies. Chen et al. (2020) compared different optimization techniques for PID tuning in BLDC motor drives, highlighting the effectiveness of genetic algorithms. Similarly, Gupta et al. (2019) proposed a particle swarm optimization-based approach for parameter tuning, achieving better speed regulation and transient response.

Another emerging trend is the development of sensorless control techniques, which eliminate the need for physical position sensors. Kim et al. (2024) designed a sensorless control scheme using sliding mode observers, allowing accurate speed and position estimation. Wang et al. (2021) explored adaptive observers for sensorless BLDC motor control, demonstrating robust performance despite parameter variations and external disturbances.

Adaptive control techniques have also been widely explored to handle uncertainties and disturbances in BLDC motor systems. Liu et al. (2023) developed an adaptive sliding mode control strategy that effectively compensates for uncertain load torques, ensuring stable motor operation. Similarly, Chen et al. (2021) introduced a model-free adaptive control approach using iterative learning, improving tracking performance and disturbance rejection.

Robust control methodologies have gained attention for enhancing the stability and reliability of BLDC motor control systems. Jiang et al. (2022) presented a robust H∞ control scheme that considers parameter variations and disturbances, ensuring consistent performance under changing conditions. Liang et al. (2024) explored fractional-order control techniques, which provided improved robustness and stability compared to conventional controllers.
Predictive control methods have emerged as another promising approach for high-performance BLDC motor control. Wang et al. (2019) proposed a predictive torque control strategy that improved both dynamic performance and efficiency. Yang et al. (2023) demonstrated the real-time implementation of model predictive control using FPGA platforms, proving its feasibility in hardware-constrained environments.
Furthermore, researchers have developed advanced control strategies to address specific challenges in BLDC motor applications. Zhang et al. (2020) introduced an adaptive terminal sliding mode control technique, which provided fast response and robustness in uncertain conditions. Zhang et al. (2021) investigated dynamic surface control methods with input constraints, ensuring stable and efficient motor operation.
AI and machine learning integration has continued to shape BLDC motor control advancements. Liu et al. (2020) proposed an adaptive neuro-fuzzy control approach that effectively compensated for nonlinear load characteristics. Wang et al. (2019) introduced an adaptive sliding mode control with integral action, enhancing speed regulation and overall robustness.
Overall, the literature highlights a diverse range of control techniques for BLDC motors, including adaptive control, robust control, predictive control, and AI-based approaches. These advancements offer promising opportunities to improve the efficiency, performance, and reliability of BLDC motor systems in various industrial applications. By building on these findings, this study aims to contribute to the development of innovative BLDC motor control strategies that address the evolving needs of modern engineering systems.

3. METHODOLOGY

The methodology involves modeling the BLDC motor system and integrating it with the NARMA-L2 controller. The NARMA-L2 controller, equipped with hidden layers and neurons, is trained using historical data to optimize control signals. The simulation is conducted in MATLAB/Simulink, with parameters such as hidden layer size and delay inputs determined through simulation studies. Performance evaluation includes analyzing system identification results, neural network training outcomes, and comparative studies with traditional control methods.

3.1 BLDC MOTOR MATHEMETICAL MODELING

Assume that the parameters of stator windings are equivalent and constant on each phase. As shown in Figure 1,

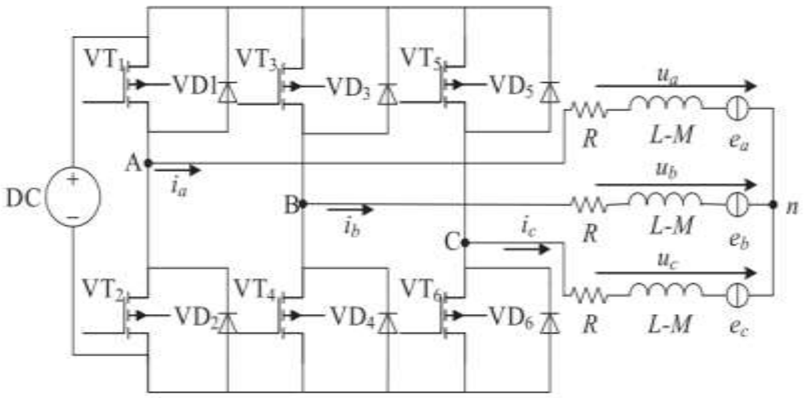

Fig. 1: BLDCM Circuit Diagram

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The voltage equations of BLDCM can be expressed as follows:

$$u_a = Ri_a + (L - M)\frac{di_a}{dt} + e_a, \quad (1)$$

$$u_b = Ri_b + (L - M)\frac{di_b}{dt} + e_b, \quad (2)$$

$$u_c = Ri_c + (L - M)\frac{di_c}{dt} + e_c, \quad (3)$$

Where, u_x, $i_x$and e_x (x = a, b, c) indicate, respectively, the voltage, current and e.m.f. of three-phase windings; R and L signify the resistance and self-inductance of each phase's windings; M denotes the mutual inductance between any two windings; and n denotes the electric potential reference point. Due to the fact that the terms of LM are evenly represented by LM in the preceding equations, the voltage equations of BLDCM may be rewritten as

$$u_a = Ri_a + L_M\frac{di_a}{dt} + e_a, \quad (4)$$

$$u_b = Ri_b + L_M\frac{di_b}{dt} + e_b, \quad (5)$$

$$u_c = Ri_c + L_M\frac{di_c}{dt} + e_c, \quad (6)$$

3.2 DESIGN OF NARMA-L2 CONTROLLER

Artificial Neural Network (ANN)-based control methods have gained popularity for their adeptness, adaptability, and efficacy in managing nonlinear systems. These techniques have seen increased application in controlling and identifying dynamic systems in contemporary research. Among these methods, the NARMA-L2 controller stands out as particularly suitable for handling time-dependent and nonlinear systems. The NARMA-L2 controller entails two primary steps: firstly, identifying the system to be controlled, and secondly, designing the system control strategy.

In the initial step of system determination, the behavior of the nonlinear discrete-time system is scrutinized, as delineated in Eq. 7.

$$y(k+d) = N(y(k), y(k-1), \ldots, y(k-n+1), u(k), u(k-1), \ldots, u(k-m+1)) \quad (7)$$

In Eq. 7, u(k) represents the system input and y(k) denotes the system output, with m and n denoting the measured delay values of the inputs and outputs, respectively, and d representing relative degrees. Multilayer neural networks are employed to define N nonlinear functions.

When the system follows a reference, the nonlinear controller can be expressed as shown in Eq. 8. The G function, which minimizes the mean square error, can be determined through neural network training utilizing the back-propagation algorithm. Consequently, the NARMA-L2 controller can be derived as depicted in Eq. 9.

$$u(k) = G(y(k), y(k-1), \ldots, y(k-n+1), y_r(k+d), u(k-1), \ldots, u(k-m+1)) \quad (8)$$

$$\hat{y}(k+d) = f[y(k), y(k-1), \ldots, y(k-n+1), u(k-1), \ldots, u(k-m+1)] + g[y(k), y(k-1), \ldots, y(k-n+1), u(k-1), \ldots, u(k-m+1)].u(k) \quad (9)$$

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The advantage of this form of reference system outputs can be solved for the control input that causes the tracking. The obtained controller is shown in Eq. 10.

$$u(k)=\frac{y_r(k+d)-f[y(k),y(k-1),\ldots,y(k-n+1),u(k-1),\ldots,u(k-n+1)]}{g[y(k),y(k-1),\ldots,y(k-n+1),u(k-1),\ldots,u(k-n+1)]} \tag{10}$$

However, it is not practical to define the input that depends on the output. For this reason, Eq. 11 is used for system definition for d ≥ 2.

$$\begin{aligned} y(k+d) &= f[y(k),y(k-1),\ldots,y(k-n+1), \\ &u(k),u(k-1),\ldots,u(k-n+1)] + g[y(k),y(k-1),\ldots,y(k-n+1),u(k), \\ &u(k-1),\ldots,u(k-n+1)].u(k+1) \end{aligned} \tag{11}$$

The NARMA-L2 controller is obtained as shown in Eq. 12

$$u(k+1)=\frac{y_r(k+d)-f[y(k),\ldots,y(k-n+1),u(k),\ldots,u(k-n+1)]}{g[y(k),\ldots,y(k-n+1),u(k),\ldots,u(k-n+1)]} \tag{12}$$

The fundamental structure of the NARMA-L2 controller is depicted in Figure 2, showcasing its simplest form with just one neuron in the hidden layer. However, practical applications often necessitate multiple neurons in this layer. Moreover, the number of delayed inputs plays a crucial role since the system model's degree is typically unknown. Following the completion of the training process, the NARMA-L2 controller must be integrated with the system, as depicted in Figure 3.

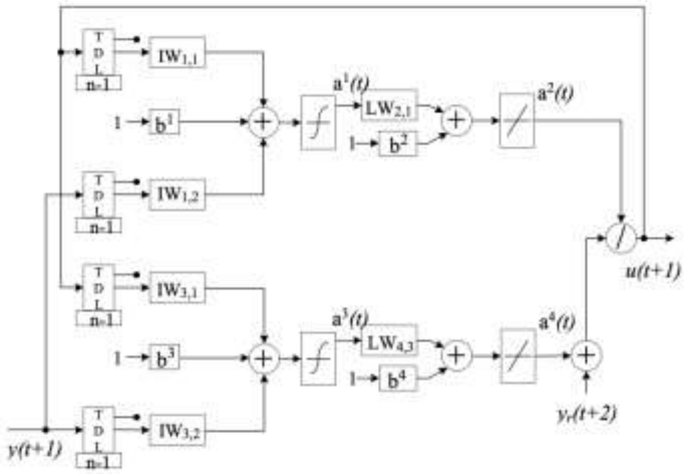

Fig. 2: NARMA-L2 Controller

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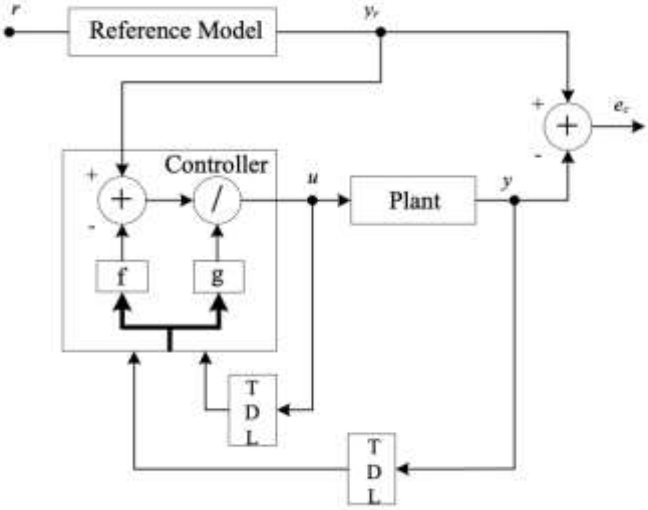


Fig. 3: The block diagram of NARMA-L2 Controller Connected the System

4. SIMULATION RESULTS

The simulation is conducted using the MATLAB/Simulink environment. In this study, the configuration of the hidden layers is set to 20, with 3 delay inputs and 2 delay outputs. These parameters are typically determined through simulation studies. The network's sample time is set to 0.001s, and the neural network is trained on 10,000 data input-output pairs within this time frame. Figure 4 illustrates the results of system identification and neural network training in the MATLAB/Simulink environment. Specifically, Figure 5 presents the system input and output, neural network output, and the error between the system output and neural network output.

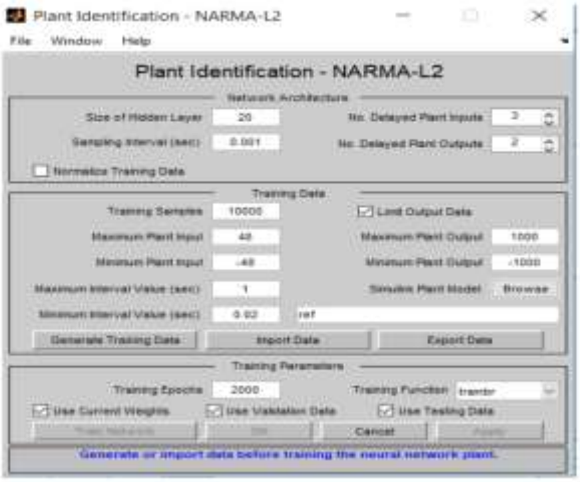
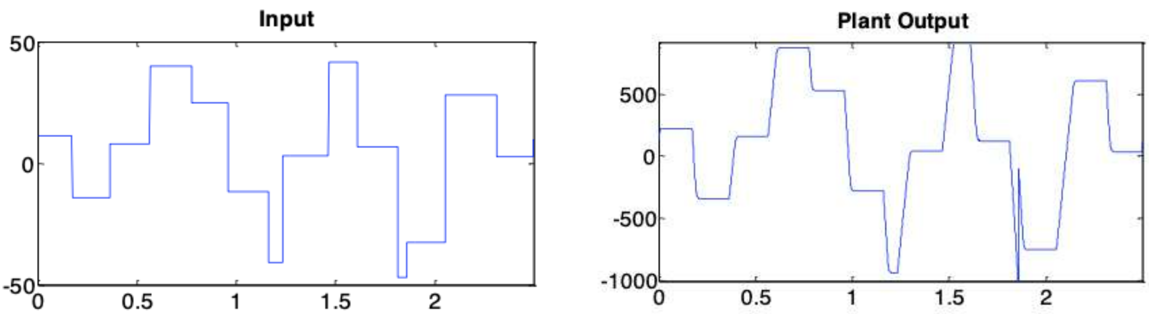
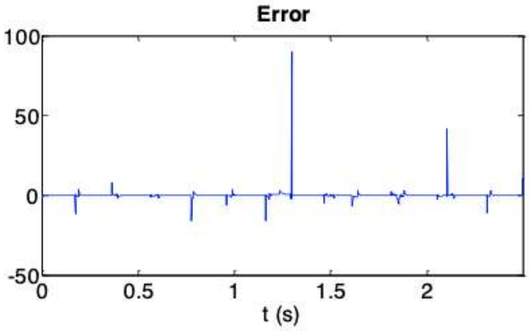


Fig. 4: Plant identification of the NARMA-L2 and NN training in MATLAB/Simulink environment

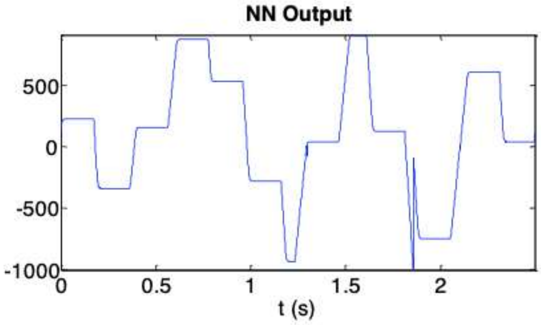


(a)

(b)



(c)



(d)

Fig.5: The system input, the plant output, the NN output and error between plant output and NN output after the NN training

5. Conclusion

This study presented a novel approach to BLDC motor control using the NARMA-L2 model, an Artificial Neural Network-based technique. Through MATLAB simulations, the proposed NARMA-L2 controller demonstrated superior performance compared to conventional control methods, offering improved speed regulation, torque response, and overall system stability. By utilizing historical data and incorporating exogenous inputs, the NARMA-L2 model effectively predicts system behavior and generates precise control signals.

The results highlight the potential of AI-driven control strategies in enhancing BLDC motor performance, with practical implications for industries requiring precise and efficient motor control. Future research could focus on further refining the NARMA-L2 controller and evaluating its real-world implementation in BLDC motor systems to validate its effectiveness beyond simulation.

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