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Performance analysis of intelligent controllers for permanent magnet synchronous motor drive systems

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ABSTRACT

Permanent magnet synchronous motors (PMSMs) are utilized in robotics and automation applications due to their exceptional performance, compact dimensions, and minimal maintenance needs. To ensure dynamic operation and achieve outstanding performance, accurate rotor position detection and real-time control methods are required, independent of the motor's mathematical model. Several intelligent controllers based on soft-computing tools were designed and tested to evaluate the performance of the PMSM drive system. The performance of these intelligent controllers was compared to that of a conventional proportional-integral-derivative (PID) controller, which adjusts its parameters according to the mathematical model of the PMSM. The results indicate that the proposed intelligent controllers outperform the conventional PID controller in controlling the speed of the PMSM. The deep learning-based controller achieved the best results among all evaluated controllers, demonstrating rapid response, minimal overshoot (less than 0.35%), and improved capabilities for handling disturbances or changes in motor parameters.

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1. INTRODUCTION

Over the past three decades, permanent magnet synchronous motors (PMSMs) have emerged as a key component in automation and robotics systems, particularly those requiring high precision [1]. These motors are ideal for applications demanding precise control and reliable performance due to their high efficiency, compact design, and low maintenance requirements [2]. However, controlling these motors requires a precise rotor position detection unit and an efficient control system that is not based on a mathematical model of the motor [3]. Because PMSM drive systems are dynamic, effective control strategies are essential to maintain the desired performance, especially under varying operating conditions, disturbances, and uncertainties inherent in some automation and robotics applications. Traditional controllers, such as proportional-integral-derivative (PID) controllers, are widely used in PMSM drives due to their simplicity and ease of implementation [4], [5]. However, these controllers require continuous parameter adjustments, making them less appropriate for robotic systems [6]. Advanced controllers based on accurate mathematical models of PMSMs have also been implemented [7].

PMSM motors also face several technical and practical challenges that may limit their performance or applicability in robotics and automation. These motors require sophisticated control algorithms to ensure efficient and accurate performance. Such controllers require precise rotor position feedback and an accurate mathematical model [3], [8]. The majority of PMSMs depend on position or speed sensors for effective operation. However, sensors increase costs and sometimes fail in harsh environments caused by dust, vibration, and changes in temperature. Sensorless control approaches have been developed [9]; however, they generally exhibit reduced reliability at low speeds or at startup, which is essential for robotics applications requiring smooth and precise control at low velocities.

Developing intelligent controllers that have no dependence on an accurate model of the PMSM drive is the goal of this study. It will go over how four controllers that use soft computing approaches were designed and evaluated. The fuzzy logic controller (FLC), the artificial neural network (ANN)-based controller, the adaptive neuro-fuzzy inference systems (ANFIS)-based controller, and the deep learning (DL)-based controller are being discussed here. A comparison will be made between the performance of the proposed intelligent controllers and that of traditional PID controllers. The purpose of this comparison is to illuminate the benefits and possibilities of intelligent controllers in terms of obtaining superior control performance for PMSM drive systems. The study aims to illustrate that intelligent control strategies provide viable solutions to address the shortcomings of traditional control methods, hence facilitating reliable, efficient, and adaptive control of PMSM drives, particularly in automation and robotics applications.

The research framework is outlined as follows: the next part examines the relevant literature review. Section 3 covers the fundamental details of the PMSM system components. Section 4 addresses the use of a conventional PID controller for PMSM drives. Section 5 discusses the application of soft computing techniques in the development of intelligent controllers. Section 6 presents the outcomes, evaluations, and comparisons of various control methodologies. The primary conclusion and suggested future work are summarized in the final section.

2. LITERATURE REVIEW

PMSMs suffer multiple challenges that may restrict their performance or use in robotics and automation. Advanced control algorithms based on precise mathematical models of PMSMs are extremely challenging to ensure efficient and accurate operation. Achieving adequate performance in real-time systems can be challenging, as most controllers require frequent parameter modifications [10]. To solve these issues, advanced controllers have been suggested, such as direct torque control [11], [12], and adaptive control [13] each aimed at overcoming the deficiencies of traditional control techniques. Youssef *et al.* [14] examined nonlinear control strategies for PMSMs, highlighting their effectiveness in managing inherent nonlinearities and dynamic complexities. Ullah *et al.* [15] investigated traditional PI control, predictive current control (PCC), and slide mode control (SMC), outlining their various strengths and drawbacks. Despite their increased complexity, PCC and SMC are especially recognized for their robustness and efficiency in disturbance management. Peng and Yao [16] presented the analysis of predictive control systems, which are becoming more popular for their ability to enhance performance within restrictions.

Most of these controllers depend on the use of mathematical models of PMSM dynamics for the purpose of controller design and updating of its parameters [17]. To reduce this dependency, further research has investigated intelligent control techniques, including genetic algorithms [11], fuzzy logic [18], and neural networks (NN) [12], for the design and modification of controller settings. Chen *et al.* [19] proposed a variable fractional-order fuzzy SMC that improves PMSM speed control in the presence of disturbances, demonstrating superior robustness and reduced overshoot relative to the PID controller. Xin *et al.* [20] proposed a controller that combines sliding mode control with a load torque observer and fuzzy logic, resulting in faster recovery and significantly less chattering relative to sliding mode and PID controllers.

Guo and Wen [21] introduced a methodology using particle swarm optimization to automatically adjust fuzzy PI membership functions, resulting in enhanced dynamic speed response and improved resistance to load fluctuations. Rajesh and Sebasthirani [22] developed a fractional-order PID controller for PMSMs, optimized by genetic algorithms and recursive backpropagation learning, resulting in minimal overshoot, faster settling time, and higher accuracy. Stumper *et al.* [23] introduced a real-time model predictive control technique for PMSMs using quadratic cost minimization, resulting in smooth torque dynamics, effective field-weakening, and quick response. Peng and Yao [16] provided an extensive study of model predictive control (MPC) systems applied for PMSMs in industrial applications.

Soft-computing tools have been used to design and develop intelligent controllers that do not rely primarily on mathematical models of PMSMs. These intelligent controllers are capable of improving control in complex and changing environments using artificial intelligence [10]. Various controllers have been implemented to control the speed and position of PMSMs, including controllers based on ANN [18], [24], controllers based on adaptive neural fuzzy inference systems (ANFIS) [3], [12] controllers based on DL [3], [25], and deep reinforcement learning techniques [26]–[28]. These controllers are characterized by their high efficiency in handling uncertainty and nonlinearity, as well as their ability to learn from past experiences and adapt to new conditions. As a result, intelligent controllers offer improved performance, particularly in terms of accuracy, robustness, and resistance to disturbances and changes in system parameters. Anbalagan and Senthilnathan [29] provided a comprehensive review of a number of classical and intelligent control strategies for PMSMs, including PID, direct torque control, and field-directed control, as well as advanced techniques such as SMC, NN-based control, FLC, ANFIS, and MPC [30]. The research highlights their efficiency, robustness, and difficulties of implementation. Khiabani and Heydari [24] developed an adaptive dynamic programming controller using actor–critic NNs within the scope of learning-based and adaptive control techniques. This controller demonstrated enhanced torque and speed control under uncertain load conditions, outperforming both field-oriented and direct torque control strategies. Lin *et al.* [31] introduced a machine learning-based control strategy using distributed Gaussian process regression to simulate unknown system dynamics, allowing real-time control with ensured stability through Lyapunov techniques. This literature review on PMSM control concludes that soft-computing tools offer effective control strategies independent of precise mathematical models. PMSM models are often challenging to obtain in dynamic situations. Such situations include robots and automation.

3. ELEMENTS OF PMSM DRIVE SYSTEM

A sensorless drive system is an electric motor drive system that operates without any use of mechanical sensors. Sensorless drives are widely used in robotics, automation, electric vehicles, drones, and domestic appliances. The sensorless drive system consists of a PMSM, an implicit rotor position detector, a pulse width modulation (PWM) inverter, and a microcomputer, as seen in Figure 1.

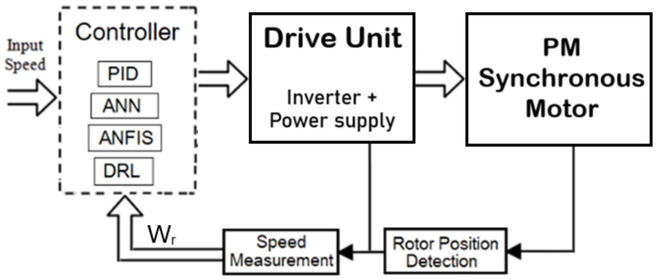

Figure 1. Layout of a PMSM drive system

3.1. PMSM motor

A PMSM is an electric motor with a constant magnetic field created by permanent magnets embedded in the rotor. The stator generates a rotating magnetic field using alternating current, causing the rotor to align with the stator's magnetic field at a constant velocity [2], [3]. The main features of PMSMs that make them ideal for automation, robotics, and servo-drive applications include their compact size, minimal maintenance needs, rapid and reliable dynamic response, accurate speed and position control, higher efficiency, and considerable torque density.

For testing the performance of AI-based controllers compared with traditional controllers, a dynamic model of a PMSM was created based on its electrical and mechanical operating equations, as shown in Figure 2. The transfer function of the PMSM used in this study is given by [7]. Where Wr is the rotor angular velocity and V is the applied voltage. The motor parameter values are listed in Table 1. Based on these parameters, the transfer function of the PMSM used in this study is given by (1).

$$\frac{W_r(s)}{V(s)} = \frac{4.705S+2.219}{S^3+7.504S^2+3.36S+2.702} \tag{1}$$

3.2. Drive unit

A motor drive unit consists of an inverter, a power supply, and a local controller. PMSMs need a variable-frequency, variable-voltage alternating current source to effectively control their speed and torque. The inverter converts direct current (DC) voltage into a three-phase alternating current (AC) supply necessary for the PMSM. The inverter carefully controls motor speed by adjusting the output frequency. By changing the inverter output voltage, the required torque can be achieved.

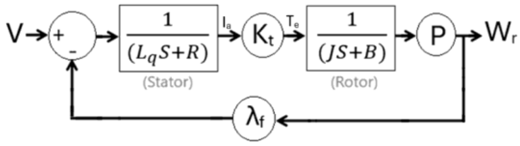

Figure 2. Block diagram of a PMSM model

Table 1. Parameters of a PMSM

Parameter	Value
Torque constant (Kt)	6.807 Nm/amp
Mutual flux between magnet and stator (λf)	1.513 V/rad/sec
Moment of inertia (J)	0.0337 Kg.m^2
Stator resistor (R)	0.12 Ω
Quadrature axis inductance (Lq)	0.764 mH
Friction coefficient (B)	0.086
Pole pairs (P)	2

3.3. Rotor position detection

To develop an efficient and high-performance PMSM drive system, precise rotor position detection is essential, as the initial torque is significantly affected by the accuracy of rotor positioning [6]. Several methods exist for rotor position detection in PMSM drive systems, some employing explicit sensors, and others using implicit sensors. Optimal rotor position detection can be achieved by accurately determining the rotor magnet's position relative to the stator windings. When the stator is fed by an inverter, explicit sensors may not accurately display the rotor magnet's position. In such cases, implicit sensors are the more suitable option for rotor positioning [2]. Subsequently, the position and speed of the PMSM motor are determined using the outputs of the rotor position detection unit.

3.4. Computing unit

The computing unit is an essential part of any drive system, involved in executing measurement, control, and management algorithms. Microcomputers are used to implement real-time algorithms in this unit. They also enable interaction with other units, both internally and outside the system.

4. CONVENTIONAL CONTROL METHODS

Several control strategies are applied to improve the efficiency of PMSM drives during varying operating situations. The selection of the approach is based on the expected outcome features. Among the different approaches that have been suggested are those that are based on mathematical models and those that make use of artificial intelligence. This study examines conventional and AI-driven control strategies for PMSM drives. Conventional control methods for PMSM drives typically include PID controllers, direct torque control, sliding-mode control, and field-oriented control [13]. These methods may be suitable for applications that do not require high performance. However, they typically suffer from insufficient flexibility, low accuracy, and the need for frequent adjustments to controller parameters due to disturbances and changes in motor parameters. Therefore, they usually depend on a precise mathematical model of the PMSM to ensure optimal performance. Conventional PID controllers are the most widely used in industrial applications due to their simplicity and reliability. The conventional PID control law is expressed as (2).

$$U(t) = K_p e(t) + K_i \int e(t)dt + K_d \frac{de(t)}{dt} \quad (2)$$

One of the main challenges in using PID controllers in drive systems is the need for continuous parameter adjustments to accommodate dynamic system behavior. Several tuning methods exist to achieve this, including system response evaluation, heuristic approaches, and manual tuning. The Ziegler-Nichols method is a common tuning approach that involves adjusting the step response test to determine the initial PID parameters. This method can improve system performance and stability either through direct observation of the step response or through calculations based on maximum gain and oscillation period. For the purpose of comparing the performance of the controllers proposed in this study for controlling the speed of a PMSM, the optimal parameters for the PID controller were selected as follows: the proportional gain (P) was set to 3.8689, the integral gain (I) was set to 0.6573, the differential gain (D) was set to 0.2176, and the filter coefficient, M, was set to 16.036.

Optimal application of this technique requires a thorough analysis of the system's dynamics to ensure accurate parameter adjustments. These systems exhibit insufficient flexibility, low accuracy, and require frequent parameter adjustments due to changes in motor parameters. Therefore, they typically rely on an accurate mathematical model of the PMSM to ensure optimal performance.

5. INTELLIGENT CONTROL METHODS

PMSM drives are dynamic systems that show non-linear characteristics in their features. Soft computing systems can discover and manage these nonlinearities in an effective manner, allowing for smoother and more precise control compared with standard linear controls. Intelligent controllers show more sensitivity to variations in system parameters relative to conventional controllers. In high-performance drive applications, adaptive controllers are a challenging modern control approach. Thus, AI-driven controllers can offer accurate and fast responses while managing complicated nonlinear dynamics. The following types of AI-driven controllers will be analyzed.

5.1. Neural network-based controller

As can be seen in Figure 3, an ANN is used as a parallel simulation tool to construct an intelligent controller for the PMSM drive. ANNs offer a more efficient alternative to classical controllers. This is accomplished by employing a supervised multi-layer feedforward ANN trained through back-propagation. The ANN architecture contains an input layer, an output layer, and one or more hidden layers. Determining the ideal number of hidden layers and nodes involves an iterative testing process. The developed controller has a two-node input layer (denoting the error and the change in error), a hidden layer with one hundred nodes, and a single-node output layer. The dataset was partitioned into training (70%), validation (15%), and testing (15%) subsets.

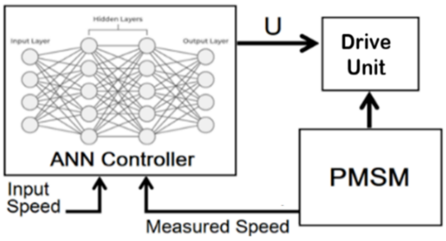

Figure 3. Layout of the NN-based controller of PMSM drive

5.2. Fuzzy logic controller

Fuzzy logic algorithms have been employed to mimic specialized knowledge and experience in the creation of controllers that compete with conventional controllers. Figure 4 displays a fuzzy logic system designed to control the speed of a PMSM drive. The fuzzy controller comprises four core elements: fuzzification, a rule database, an inference engine, and defuzzification. Each input variable (error and its derivative) is identified by seven fuzzy sets. The input and output variables are linked through 49 IF-THEN fuzzy rules, as illustrated in Table 2.

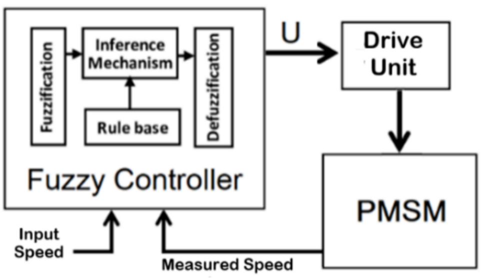

Figure 4. Layout of a fuzzy control of PMSM drive

Table 2. Rules for the fuzzy controller rules

e/Δe	Very very low	Very low	Low	Medium	High	Very high	Very very high
Very very low	Very very low	Very very low	Very low	Low	Medium	High	Very high
Very low	Very very low	Very low	Low	Low	Medium	High	Very high
Low	Very low	Very low	Low	Medium	Medium	High	Very high
Medium	Low	Low	Medium	Medium	High	High	Very high
High	Medium	Medium	Medium	High	High	Very high	Very very high
Very high	High	High	High	High	Very high	Very high	Very very high
Very very high	Very high	Very high	Very high	Very high	Very very high	Very very high	Very very high

5.3. Adaptive neuro-fuzzy inference system-based controller

The ANFIS is a hybrid model that integrates the learning powers of ANNs with the reasoning and flexibility features of fuzzy logic, especially in managing vague or incomplete facts. ANFIS-based controllers can adapt to varying operating conditions and dynamic behaviors in PMSM drives, making them extremely ideal for industrial applications. An essential benefit of ANFIS in PMSM drives is its capacity to learn from operational data, hence enhancing control performance over time without requiring manual calibration of controller parameters. ANFIS-based controllers provide robust and adaptive control, successfully solving the inherent complexity and nonlinearity of PMSM drives, hence improving overall system performance.

Figure 5 illustrates the structure of the implemented ANFIS-based controller. The design employs a set of fuzzy logic rules, as outlined in Table 3, to correlate input variables, error and change in error, with the output. Each input is characterized by five fuzzy sets, yielding 25 fuzzy rules that describe the relationship between inputs and output. The network improves these rules through training, increasing its ability to manage complicated nonlinear control tasks.

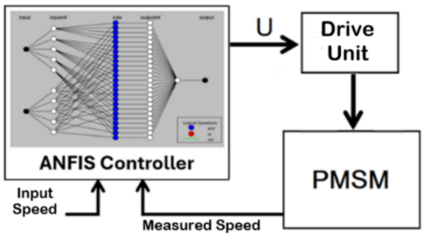

Figure 5. Layout of ANFIS-based controller of PMSM drive

Table 3. Fuzzy rules of the ANFIS model

e/Δe	Very low	Low	Medium	High	Very high
Very low	Very low	Very low	Low	Low	Medium
Low	Very low	Low	Low	Medium	Medium
Medium	Low	Low	Medium	Medium	High
High	Low	Medium	Medium	High	High
Very high	Medium	Medium	High	High	Very high

5.4. Deep learning-based controller

An AI model that uses DL to operate a PMSM can recognize complex patterns and provide predictions based on acquired data [28]. The basic framework of a DL-based controller is illustrated in Figure 6, which includes the following steps:

i) Data collection: a large dataset related to the operational performance of the drive system is collected.
ii) Data processing: the gathered data is subjected to preprocessing and is partitioned into training, validation, and test sets.
iii) Feature engineering: important characteristics affecting motor performance are recognized, and input-output pairs for controller functionality are produced.
iv) Model selection: a long short-term memory (LSTM) network is selected for its capacity to keep long-term dependencies, thus eliminating the problem of gradients disappearing. LSTM networks utilize memory cells and gating techniques to control the time-based flow of information.
v) Model training: the model is developed with input-output pairings, modified by loss functions and backpropagation. The performance is verified using a separate dataset.

vi) Model integration: the learned DL model is included in the PMSM drive system, enabling real-time prediction of control actions.
vii) Real-time control: the DL-based controller continuously monitors and improves the drive system, guaranteeing compliance with performance criteria.
viii) Controller performance improvement: the model receives periodic retraining with updated data to adjust to changing motor behavior or operational conditions.

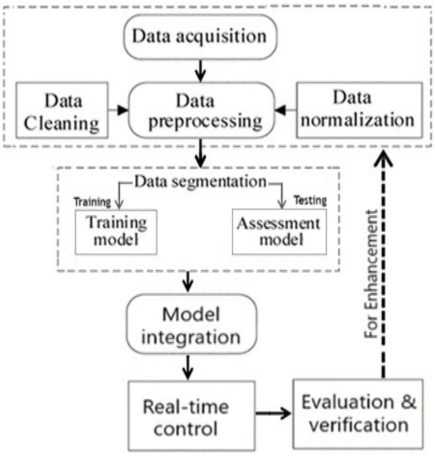

Figure 6. Layout of the DL-based controller

The design of the DL-based controller is illustrated in Figure 7. This controller gets its powerful capabilities from a deep network consisting of six hidden layers. This level of depth, when combined with activation functions, enables the model to acquire knowledge of complicated and nonlinear patterns directly from the data. The first layer of the network is a two-dimensional input layer, which is responsible for normalizing sequential data. After that, the information travels through the six hidden layers, which are composed of three fully connected layers with 200 hidden neurons and three special activation layers (tanh, leaky rectified linear unit (ReLU), and truncated ReLU), before arriving at the output. The output layer is a regression layer that integrates features from previous layers to identify complex patterns. In regression issues, the output dimension refers to the quantity of response variables.

In sequential input, fully connected layers function autonomously at each time step. The hyperbolic tangent (tanh) activation function is utilized on the layer inputs, transforming any real value to an output within the range of -1 to 1. The leaky ReLU layer executes a threshold operation by scaling negative inputs with a constant factor, whereas the clipped ReLU layer deletes values below zero and limits values over a specified maximum. This clipping minimizes output size, hence enhancing model stability. Calculating the half-mean-squared-error loss is the responsibility of the regression layer. When it comes to typical regression tasks, this layer is placed after the final fully connected layer positioned in the hierarchy. The general parameters of the implemented DL algorithm are illustrated in Table 4.

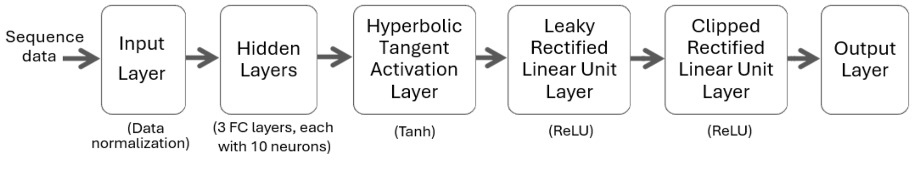

Figure 7. Structure of the DL-based controller

Table 4. Parameters of the DL algorithm

Parameter	Value
Number of hidden layers	6
Number of epochs	500
Learning rate	0.001
Validation frequency	30
Mini-batch size	1

6. RESULTS AND DISCUSSION

PMSMs are commonly used in industrial applications for their superior efficiency, compact dimensions, and minimal maintenance needs. The efficacy of these motors is mainly dependent upon the precision of rotor position detection and the chosen control approach. This study evaluates the efficiency of PMSM using four intelligent controllers and comparing their outcomes with those of a traditional PID controller under similar operating situations. Specific requirements of each application should be taken into consideration while selecting the control algorithm that is most appropriate for that application. Due to their natural complexity and nonlinearity, PMSM drives require intelligent control solutions. Both the internal dynamics and the exterior disturbances can be effectively managed by these methods. Evaluation of all five controllers was carried out under identical settings, and the results of the simulation showed that there were significant differences in the performance of each of them. Table 5 outlines the performance metrics of the five controllers evaluated with the PMSM, presenting the following outcomes:

i) FLC, ANFIS, and DL-based controllers demonstrated the ability to achieve smoother speed responses with minimum overshoot, hence enhancing the control of system dynamics.
ii) The PID and NN-based controllers had comparable performance, while the NN controller was somewhat less successful.
iii) The FLC and ANFIS-based controllers produced comparable results across most measures, except for overshoots, in which the FLC showed a lower value.
iv) The DL-based controller provided the lowest steady-state error, minor overshoot, and the shortest rise and settling periods from all the other controllers. It also outscored all the other controllers in every performance metric.

Table 5. Comparative analysis of controller performance

Controller	ITAE	IAE	ISE	Overshoot %	Rise time (s)	Peak time (s)
PID	1.508	0.5612	0.1723	4.734	0.613	1.5
NN	1.51	0.5866	0.1766	5.851	0.608	1.448
FLC	1.945	0.4712	0.1654	3.846	0.536	1.383
ANFIS	1.945	0.4712	0.1654	4.521	0.536	1.383
DL	0.6801	0.1278	0.0449	0.348	0.118	0.5

Figure 8 demonstrates the timing response of the five controllers and their efficacy in achieving and keeping a rotational velocity of 1 rad/s. The DL-based controller exhibited superior performance, indicated by its quick response, minimal overshoot, and minimal settling time. This controller demonstrated superior performance. The finely calibrated PID controller demonstrated an effective response, but with a marginally increased overshoot. The performance of the NN-based controller during the transient phase was inefficient for overshoot and settling time, indicating a need for more training. In comparison to the DL-based controller, the performance of the ANFIS and FLC controllers is almost similar; however, the DL-based controller demonstrates minimized overshoot and quicker stabilization than the other controllers.

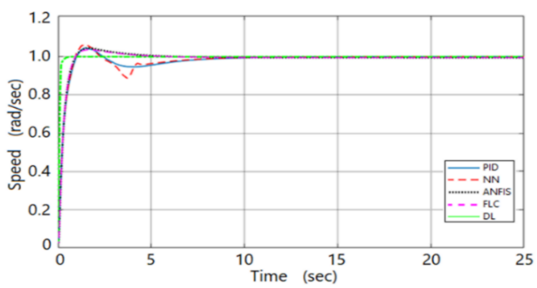

Figure 8. Time response of PMSM speed without disturbances

As shown in Figure 9, the five controllers were tested for their capacity to deal with external disturbances or motor parameter changes. DL-based controller (green line) performed best among the controllers tested. A DL-based controller can quickly follow speed command with little transient overshoot, handle disturbances, and stabilize in the shortest time. The other controllers performed weakly in various applications that need high-precision motor speed or position control, particularly in overshooting and handling disturbances or motor parameter changes.

The five controllers were evaluated under a step-like torque disturbance ranging from 0 to 5 Nm. Due to the disturbance, the motor speed initially decreases, after which the controller adjusts the change. Figure 10 illustrates that the DL-based controller effectively manages disturbances and keeps a steady speed, whereas other controllers require extra time to return the speed to the desired value.

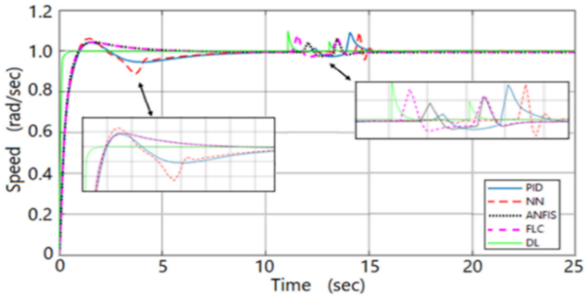

Figure 9. Speed response of a PMSM with disturbances

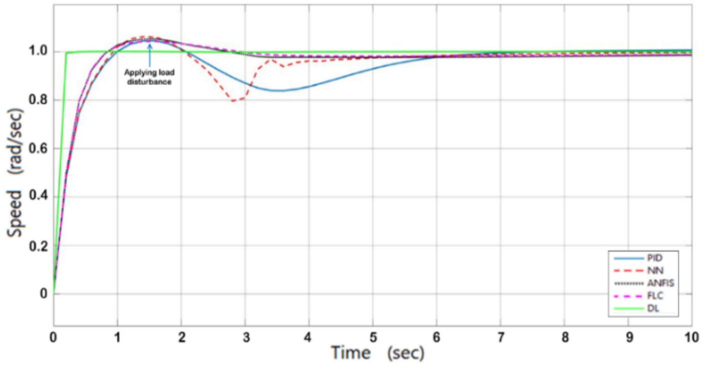

Figure 10. Speed response of a PMSM with load torque disturbance

By comparing the control signals and speed response signals of the DL-based controller and the traditional PID controller, as shown in Figures 11 and 12, the dynamic performance of the system depends greatly on the tuning of the PID parameters, which may lead to overshoot and slow response. In DL controllers, the control signal is generated by a NN trained on a dataset representing the different operating conditions of the PMSM. The comparison evaluation concludes that the DL-based controller demonstrates enhanced overall performance. Its ability to achieve rapid stability with minimum overshoot and notable disturbance rejection makes it the most efficient controller among those examined.

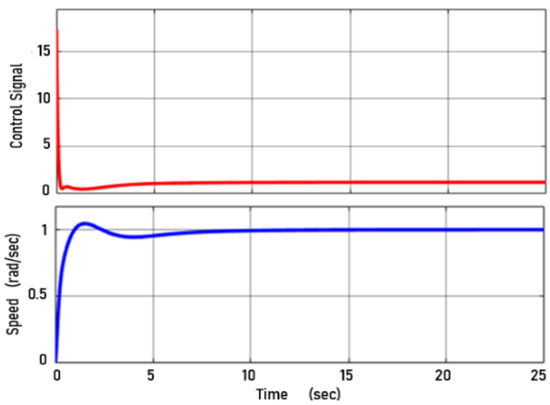

Figure 11. Control signal and speed response of a PMSM with PID controller

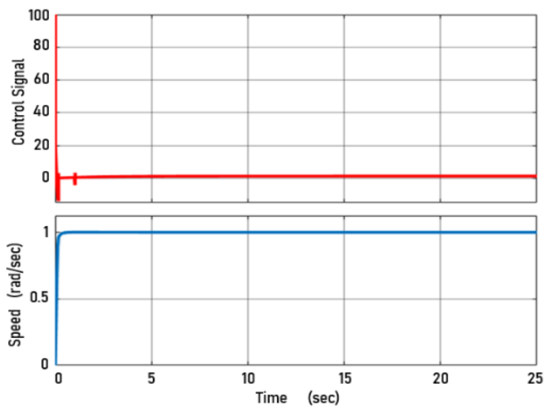

Figure 12. Control signal and speed response of a PMSM with DL-based controller

7. CONCLUSION

PMSMs are gaining popularity in robotics and automation systems due to their superior efficiency, compact design, as well as less maintenance needs compared to other electrical machines. Effective control of these motors requires precise rotor position detection and an adaptive controller capable of handling system dynamics and external disturbances. Conventional controllers of PMSM mainly depend on mathematical models of the motor, requiring regular modifications of its parameters, particularly in real-time applications. This study outlines the design and assessment of four intelligent, model-free controllers for PMSM drives, including an FLC, an NN-based controller, an ANFIS-based controller, and a DL-based controller. The efficiency of these intelligent controllers was evaluated against that of a conventional PID controller under similar settings. The results indicated that the FLC, ANFIS, and DL-based controllers provided faster and steadier responses compared to a conventional PID controller. The DL-based controller shows enhanced performance, successfully handling external disturbances and variations in parameters. It is distinguished by its ability to control motor speed with minimal overshoot (less than 0.35%) and a settling time of about 20% faster than that of other controllers. DL-based controllers are extremely effective in PMSM drive systems, as they can model complicated control dynamics, adapt to varying operating conditions, and continually learn from system behavior, making them flexible, tolerant, and efficient solutions for real-time applications.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
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R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

This study did not involve human participants or animals and therefore did not require ethical approval. All procedures were conducted in accordance with relevant institutional and national guidelines.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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