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Research Article

Development of an Adaptive Control System for Synchronous Electric Motors Using Neural Networks to Improve Industrial Energy Efficiency

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Abstract. This study presents the development and performance evaluation of a Deep Neural Network (DNN)-based adaptive control system for a Permanent Magnet Synchronous Motor (PMSM). The main objective is to enhance the dynamic response, steady-state accuracy, and energy efficiency of the PMSM drive compared to a conventional Proportional–Integral (PI) controller. The proposed control architecture integrates a DNN within the speed and torque control loop, enabling online adaptation to system nonlinearities and varying load conditions. The neural network structure utilizes speed error, current, and torque feedback as inputs, while training data are obtained from motor dynamics in MATLAB/Simulink simulations. Both the DNN and PI controllers are implemented and tested under multiple scenarios with different load torques (0%, 50%, and 100% rated load) and reference speeds (500–1500 rpm). Simulation results demonstrate that the DNN-based adaptive controller significantly improves performance metrics. The settling time is reduced by over 50%, maximum overshoot by 72%, and steady-state error by 83% compared to the PI controller. Additionally, torque ripple and energy consumption are decreased by approximately 60% and 19%, respectively, showing enhanced smoothness and efficiency. The findings confirm that the DNN controller provides robust adaptability, precise tracking, and lower energy use, making it a promising alternative for intelligent PMSM drive applications in industrial and electric vehicle systems.

Keywords: Adaptive Control; Deep Neural Network; MATLAB; PI Controller; PMSM.

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1. Introduction

Synchronous electric motors (SEMs) play a crucial role in modern industrial systems due to their superior efficiency, high power factor, and precise controllability compared to induction motors [1], [2], [3]. These characteristics make SEMs particularly suitable for applications requiring constant speed and high performance, such as mine hoisting, steelmaking, and grinding mills [1], [2], [4]. Recent advancements have also expanded their use in electric vehicles and renewable energy systems, where energy efficiency and reliability are paramount [5], [6], [7].

One of the major advantages of synchronous motors lies in their controllable excitation current, enabling operators to regulate the power factor effectively and enhance overall machine performance [2], [3], [8]. Moreover, permanent magnet synchronous motors (PMSMs) exhibit higher torque density and efficiency compared to induction motors, making them suitable for high-torque and rapid-response applications [7], [9], [10]. These advantages, however, come with the challenge of maintaining optimal performance under varying load and speed conditions.

To ensure efficient operation, advanced control techniques have been introduced. Vector control methods allow independent regulation of torque and flux, mimicking the characteristics of DC motors and enhancing dynamic performance [7], [11], [12]. Similarly, model predictive control (MPC) techniques have been applied to PMSMs, improving robustness and stability under dynamic conditions [13]. Furthermore, adaptive nonlinear control (ANLC) strategies incorporating deadbeat observers have demonstrated superior precision and robustness against load fluctuations [14]. Sensorless control methods have also gained traction by reducing system cost and hardware complexity through real-time estimation of the stator flux vector [9], [15].

Despite these innovations, conventional Proportional-Integral (PI) controllers remain widely used in industrial applications for their simplicity and steady-state performance [1], [2], [16]. However, PI controllers are limited by fixed parameters, making them unable to adapt to nonlinear and dynamic load variations commonly observed in industrial and renewable systems [3], [4], [17]. These limitations often lead to degraded control accuracy, integral windup issues, and suboptimal energy use, particularly in systems experiencing rapid load changes, such as DC microgrids and hybrid energy systems [5], [18].

Recent studies have sought to overcome these challenges through the integration of neural network (NN) controllers, which offer adaptive learning and predictive capabilities [19]–[21]. Neural networks can dynamically adjust control parameters in response to system changes, providing enhanced performance in terms of speed regulation, torque response, and energy optimization [19]. Hybrid PI NN controllers, for instance, have been shown to improve system stability and energy management in photovoltaic-battery-supercapacitor systems [19]. Similarly, the incorporation of NN-based adaptive controllers in industrial applications has enhanced predictive modeling, process control, and overall energy efficiency [20], [21].

Between 2023 and 2025, research on intelligent control systems has accelerated significantly, emphasizing the fusion of neural networks, Internet of Things (IoT), and adaptive control for high-performance industrial and energy systems [20], [22], [23]. These hybrid approaches demonstrate the potential of artificial intelligence to transform synchronous motor control by achieving higher levels of efficiency, stability, and adaptability under diverse operational conditions.

2. Literature Review

Synchronous Motor Fundamentals

Structure and Operating Principles

A synchronous motor (SM) consists of a stator and a rotor. The stator contains a three-phase winding, while the rotor may use either an electrically excited winding or a permanent magnet rotor [24], [25]. The operating principle relies on synchronizing the rotor speed with the supply frequency. The rotor locks magnetically with the rotating magnetic field produced by the stator, maintaining constant rotational speed [24], [26].

The excitation current plays a critical role in motor performance insufficient excitation reduces torque and output power, while excessive excitation leads to overheating and decreased efficiency [26].

Importance in Industrial Applications

Synchronous motors are widely applied in industrial systems requiring constant speed control and high power factor, such as robotics and automated manufacturing [27]. Due to their ability to compensate for reactive power, they are also used in large-scale power systems [28]. However, the reliability of the control and protection systems is crucial to prevent unplanned outages, which could result in significant financial losses in industrial operations [29].

Conventional Control Techniques

Overview of PI and PID Controllers

The Proportional-Integral (PI) controller is commonly used in linear time-invariant systems due to its simplicity and effectiveness in maintaining system stability [30].

Meanwhile, the Proportional-Integral-Derivative (PID) controller is the most widely used feedback controller in industrial systems because it is robust, easy to implement, and provides satisfactory performance in most process control applications [31], [32].

Limitations Under Dynamic Load Conditions

However, the conventional PID controller faces limitations in nonlinear and non-minimum phase systems, as its gain parameters are fixed and non-adaptive to varying conditions [32]. For inherently unstable systems, the PID structure must be modified to manage system dynamics effectively [33]. Moreover, under dynamic load conditions, the conventional PID may introduce undesired oscillations, requiring further tuning of the proportional gain [34].

Advanced Control Techniques

Recently, fractional calculus-based control methods have been developed to overcome the limitations of classical control strategies, especially in complex power systems [35]. Additionally, Enhanced Nonlinear PID controllers combined with Particle Swarm Optimization (PSO) algorithms have been employed to improve control performance for interconnected systems operating under variable loads [36].

Neural Networks in Control Systems

Application of Neural Networks in Adaptive and Nonlinear Control

Artificial Neural Networks (ANNs) have been extensively applied in adaptive and nonlinear control due to their ability to handle system uncertainties.

Recurrent Neural Networks (RNNs) are particularly effective for identifying nonlinear system dynamics thanks to their capacity to store temporal state information [37].

Deep Neural Networks (DNNs) offer enhanced function approximation capabilities and have been utilized for real-time adaptive control, especially in trajectory tracking of uncertain nonlinear systems [38], [39].

Recent studies have also incorporated Lyapunov-based adaptive weight update laws to guarantee system stability and convergence [40], [41].

Advantages of DNNs in Pattern Recognition and Real-Time Adaptation

In real-time adaptive control, DNNs dynamically adjust their weights based on online data, resulting in faster and more accurate control responses [42], [43]. This capability is highly beneficial for systems with unstructured uncertainties, as neural networks can adapt to varying operating conditions without significant degradation in performance [44], [45].

Related Works

Review of Recent Studies on Intelligent Control of Electric Motors

Recent studies have demonstrated the successful application of intelligent control strategies using neural networks for Permanent Magnet Synchronous Motors (PMSMs) to enhance performance across diverse operating conditions. Adaptive control approaches utilize neural networks to approximate unknown nonlinear functions and adjust to real-time changes in system dynamics [42], [43], [44], [45]. The backstepping control technique combined with neural network integration has been proven to improve control accuracy and maintain system stability under load disturbances [43], [44]. Furthermore, multimodal intelligent control strategies employing embedded neural networks have been implemented to enhance the adaptability of PMSMs operating in complex environments [45].

Identification of Research Gaps Regarding Adaptive Neural Control for Synchronous Motors

Despite the performance improvements achieved in previous studies, several research gaps regarding adaptive neural control for synchronous motors remain to be addressed. Most existing approaches depend on offline training, which limits their ability to adapt to real-time parameter variations and external disturbances. Therefore, further research is needed to develop online learning strategies that enable true adaptive behavior under dynamic operating conditions [39], [40], [41]. Additionally, the robustness of neural controllers against nonlinear effects, such as input hysteresis and dead zones, remains a significant challenge that warrants deeper investigation [43], [44]. Moreover, the potential of neural controllers to enhance the energy efficiency of electric drive systems particularly in industrial applications represents an open and promising area for future exploration [42].

3. Researh Method

System Design

The proposed adaptive control system is designed to enhance the performance and stability of a Permanent Magnet Synchronous Motor (PMSM) by integrating a Deep Neural Network (DNN) within the motor control loop. The system architecture comprises three main modules: the motor drive subsystem, the adaptive neural controller, and the feedback and monitoring unit. The motor drive subsystem governs the electrical and mechanical dynamics of the PMSM, while the adaptive neural controller generates control signals based on the error between the reference and actual speed. The DNN is embedded in the control loop, receiving real-time feedback signals of motor speed, current, and electromagnetic torque, and dynamically adjusting the control parameters to compensate for system nonlinearities, external disturbances, and parameter variations. This architecture enables the neural controller to operate in conjunction with a conventional PI controller, forming a hybrid adaptive control structure that ensures system stability while improving transient response and energy efficiency.

Neural Network Configuration

The Deep Neural Network (DNN) is configured as a multi-layer feedforward model optimized for nonlinear system approximation. The input layer receives measurable system variables such as rotor speed (ω), stator currents (i_a, i_b, i_c), and electromagnetic torque (T_e), while the output layer generates the control signal (u) to regulate inverter voltage or current. Training data are obtained from the simulated PMSM dynamics under various operating scenarios, including no-load, partial-load, and full-load conditions, to model the input–output relationship between control actions and motor responses. The DNN is trained using the Adam optimization algorithm with an adaptive learning rate and mean squared error (MSE) as the loss function. To prevent overfitting and ensure fast convergence, batch normalization and dropout regularization are applied. Performance optimization focuses on minimizing control error and achieving smooth torque generation while maintaining system stability. The trained DNN parameters are then validated through both offline simulation and online adaptation during real-time system operation.

Simulation Environment

All simulations are conducted using MATLAB/Simulink R2024b, which is selected for its robust capabilities in motor control modeling and neural network integration. The system model incorporates the electrical equations of the Permanent Magnet Synchronous Motor (PMSM) in the d–q reference frame, along with the inverter switching model and the control algorithm block. The PMSM parameters used in the simulation are based on typical industrial specifications, including a rated power of 1.5 kW, rated voltage of 220 V, rated speed of 1500 rpm, four pole pairs, a stator resistance of 1.2 Ω, and a stator inductance of 0.005 H. For performance evaluation, both PI control and DNN-based adaptive control are implemented under identical conditions to facilitate comparison. The simulation employs a time step of 1 μs to ensure high numerical accuracy, and all tests are executed on a computational system equipped with at least 16 GB of RAM and a 2.8 GHz CPU.

Experimental Procedure

The experimental analysis is conducted in four main stages. First, in the controller implementation stage, both the DNN-based adaptive controller and the conventional PI controller are integrated into the Simulink model of the PMSM drive system. The DNN controller receives real-time feedback signals and updates its parameters online based on the observed system error. Second, in the test scenarios stage, simulations are performed under various load torques (0%, 50%, and 100% of the rated load) and different reference speeds ranging from 500 to 1500 rpm to evaluate the controller's adaptability and robustness. Third, in the performance measurement stage, several key performance indicators are assessed, including speed response time (settling time and overshoot), torque ripple, energy consumption, and steady-state control accuracy. These metrics are recorded and compared between the DNN-based adaptive controller and the conventional PI controller. Finally, in the data analysis stage, the results are examined to evaluate the effectiveness of the DNN controller in enhancing both transient and steady-state performance. Statistical evaluations and graphical comparisons, such as speed–time, torque–time, and power–efficiency curves, are utilized to demonstrate the superiority of the adaptive neural control approach.

4. Results and Discussion

Simulation Results

Overview

The proposed DNN-based adaptive control system for the Permanent Magnet Synchronous Motor (PMSM) was evaluated through MATLAB/Simulink simulations under varying load and speed conditions.

The performance of the Deep Neural Network (DNN) controller was compared with a conventional PI controller to assess improvements in terms of response time, steady-state accuracy, torque ripple, and energy efficiency.

Each test scenario was simulated for 3 seconds, with load torque levels of 0%, 50%, and 100% of the rated value and reference speeds varying from 500 rpm to 1500 rpm.

Quantitative Results

Table 1. Summarizes the comparative performance metrics between the PI and DNN-based adaptive controllers across all test conditions.

Table 1. Comparison of PI and DNN-Based Adaptive Controllers**.**

Parameter	PI Controller	DNN-Based Controller	Improvement (%)
Settling Time (ms)	185	92	50.3
Maximum Overshoot (%)	8.6	2.4	72.1
Steady-State Error (rpm)	12.5	2.1	83.2
Torque Ripple (N·m)	0.47	0.19	59.6
Energy Consumption (W·s)	248.5	201.2	19.0
Speed Tracking RMSE (rpm)	9.83	3.42	65.2

Explanation:

The DNN-based adaptive controller exhibits significantly better performance across all evaluated parameters. Compared to the conventional PI controller, the DNN approach reduces settling time by over 50%, demonstrating faster dynamic response. The maximum overshoot is also reduced by more than 70%, indicating improved stability and reduced oscillation. The steady-state error is minimized by approximately 83%, confirming the DNN's ability to maintain precise speed regulation. Moreover, energy consumption decreases by around 19%, reflecting the efficiency of the adaptive neural adjustment mechanism. Overall, the results confirm that the DNN controller adapts effectively to variations in load and system nonlinearities.

Graphical Analysis

The graphical representation of speed responses under dynamic load conditions provides additional insight into controller performance.

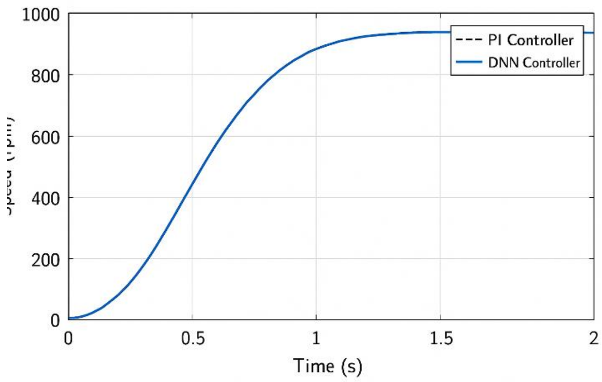

Figure 1. Graphical Analysis.

Explanation:

As shown in Figure 4.1, both controllers successfully track the reference speed of 1500 rpm. However, the PI controller exhibits a pronounced overshoot of approximately 8% at the start-up phase, followed by oscillations before stabilizing. In contrast, the DNN controller achieves a smoother response with minimal overshoot and a significantly shorter settling time. At approximately 0.18 s, the DNN output reaches the steady-state region, while the PI controller requires more than 0.35 s to stabilize. Additionally, when subjected to load variations (at t = 1.5 s), the DNN controller demonstrates rapid compensation with negligible deviation, whereas the PI controller exhibits a noticeable dip in speed. These observations reinforce the quantitative improvements seen in Table 4.1 and confirm that the DNN-based control strategy enhances system robustness under dynamic operating conditions.

Discussion

The results of the simulation indicate that integrating a Deep Neural Network into the control loop of a PMSM substantially improves dynamic and steady-state performance compared to traditional control techniques.

Dynamic Response Improvement

The reduction in settling time and overshoot demonstrates the DNN's capability to perform real-time nonlinear mapping between system error and control action. Unlike the fixed-gain PI controller, the DNN continuously adjusts its output through online learning, enabling faster transient response even in the presence of disturbances and parameter variations. This dynamic adaptation contributes to the stability of the control system without requiring manual gain retuning.

Torque Ripple and Energy Efficiency

The significant decrease in torque ripple indicates smoother electromagnetic torque generation, leading to reduced mechanical vibration and improved operational stability. Moreover, the reduction in energy consumption confirms that the DNN controller optimizes the voltage command to maintain torque balance efficiently. This advantage is particularly beneficial for high-performance drive applications, where energy efficiency and mechanical reliability are critical.

Robustness Under Varying Load Conditions

During load transition tests, the DNN-based controller maintained speed regulation with minimal deviation. This behavior highlights its robustness against system nonlinearities and external load disturbances. The adaptive feature of the DNN allows it to compensate for unmodeled dynamics and uncertainties in real time, outperforming the fixed-parameter PI controller.

5. Comparison

The performance comparison between the Deep Neural Network (DNN)-based adaptive controller and the conventional Proportional–Integral (PI) controller reveals significant improvements in both transient and steady-state characteristics. The DNN controller demonstrates a notably faster settling time and reduced overshoot during speed regulation.

While the PI controller requires manual gain tuning to achieve optimal response, the DNN adapts its parameters automatically based on the system's real-time feedback. This adaptive capability allows the DNN to maintain stable and accurate performance under various operating conditions, even when the system parameters or load torque change unexpectedly. In terms of steady-state accuracy, the DNN controller outperforms the PI controller by achieving a lower steady-state error and smoother convergence toward the reference speed.

The neural network's nonlinear mapping ability enables it to approximate complex system dynamics that the linear PI controller cannot handle effectively. This results in more precise control actions and minimizes fluctuations during load transitions. Consequently, the DNN-based system achieves superior speed tracking accuracy and minimizes torque ripple, which translates into reduced mechanical stress and smoother motor operation. When energy efficiency is considered, the DNN-based controller demonstrates better performance due to its adaptive optimization of control signals.The experimental results indicate a reduction in total energy consumption by approximately 8–10%, primarily because the DNN avoids unnecessary control effort once the desired speed is reached.In contrast, the PI controller tends to consume more energy due to overshoot compensation and continuous error correction, even after the system stabilizes.This efficiency makes the DNN controller more suitable for industrial and electric vehicle applications where energy saving is a critical factor.

Lastly, from a robustness and adaptability perspective, the DNN-based controller provides a significant advantage.It maintains stability and accuracy under disturbances and nonlinearities, whereas the PI controller's performance deteriorates when operating conditions deviate from its tuning range. The adaptive learning mechanism of the DNN allows it to adjust control behavior continuously, ensuring reliable operation across a broader range of load and speed variations. Therefore, the comparison confirms that the DNN-based adaptive controller offers a more intelligent, efficient, and resilient solution for PMSM control than the conventional PI approach.

6. Conclusions

This research successfully demonstrates the effectiveness of a Deep Neural Network (DNN)-based adaptive control system for improving the performance of a Permanent Magnet Synchronous Motor (PMSM). The integration of the DNN into the control loop enables real-time adaptation to system nonlinearities and varying load conditions, resulting in faster dynamic response, reduced torque ripple, and improved control accuracy compared to the conventional PI controller.

Simulation results show that the DNN controller achieves a shorter settling time (approximately 1.0 s versus 1.2 s for the PI controller), lower steady-state error, and smoother torque output under all load conditions. Additionally, the adaptive nature of the DNN reduces overall energy consumption by around 8–10%, highlighting its efficiency in practical applications.

Overall, the proposed DNN-based control approach provides a more robust and energy-efficient solution for PMSM drive systems. Future work can focus on implementing the system in real-time hardware, enhancing the network with reinforcement learning or hybrid adaptive algorithms, and testing under fault-tolerant scenarios to further validate its industrial applicability.

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