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DATA-DRIVEN LSTM-BASED CONTROL TO REPLACE PID FOR UNKNOWN-MODEL ELECTRIC MOTOR SYSTEMS

Purpose. To develop and validate a data-driven control strategy that replaces the conventional proportional–integral–derivative (PID) controller with a long short-term memory (LSTM) neural network for motor speed regulation in systems with unknown or complex dynamics.

Methodology. The proposed approach consists of three main stages: 1) operating the motor under a baseline PID controller and collecting operational data (setpoints, measured speeds, and control signals); 2) training an LSTM network to learn the mapping between historical setpoints, measured outputs, and the corresponding control actions generated by the PID; 3) deploying the trained LSTM model in real time as a direct controller. The experimental validation was performed on an embedded testbed comprising a fan motor, a PWM driver, an encoder, and an Arduino Mega 2560, with the LSTM model trained in PyTorch and executed online.

Findings. The LSTM-based controller successfully tracks changing setpoints and produces smoother control signals than the baseline PID. It achieves comparable or better steady-state error and a stronger correlation between control effort and motor velocity, while reducing oscillations in nonlinear operating regimes.

Originality. Unlike most prior works, where neural networks assist in PID tuning or provide state estimation, this study demonstrates the direct substitution of PID with an LSTM controller trained solely on operational data, without the need for explicit system identification or physics-based modeling.

Practical value. The proposed approach offers an effective solution for motor control in scenarios where system identification is infeasible, unreliable, or too costly. It is particularly relevant for low-cost embedded platforms and industrial applications that require adaptive, data-driven control strategies capable of handling nonlinearities and time delays.

Keywords: *LSTM, PID replacement, time-series modeling, motor speed control*

Introduction. Controlling dynamic systems with unknown or time-varying characteristics remains a central challenge in industrial automation and robotics. In electric drives, particularly alternating-current (AC) machines such as induction motors (IMs) and permanent-magnet synchronous motors (PMSMs), classical control design typically relies on mathematical models whose accuracy is difficult to guarantee, especially on low-cost or embedded platforms. In this context, the proportional-integral-derivative (PID) controller is the industry standard for speed/torque regulation due to its conceptual simplicity, low computational cost, and straightforward implementation. In well-defined operating regimes, PID controllers provide robust performance, settling quickly with limited overshoot [1–3].

Despite their ubiquity, PID controllers are sensitive to parameter variations, nonlinearities, and unmodeled dynamics, all of which are common in AC motor drives due to temperature-dependent resistances, magnetic saturation, inverter nonlinearities, and load disturbances. Manual tuning (e.g., Ziegler-Nichols) and modern auto-tuning/optimization procedures generally presuppose knowledge of plant dynamics or the ability to approximate them via step-response or frequency-domain identification. However, when sensing is limited, and the system behaves as a black box, these assumptions break down. This can lead to degraded tracking, overshoot, or even instability under disturbances or changes in operating point [2–4]. This situation motivates two complementary lines of research:

- enhanced PID-type approaches that improve robustness and adaptation;
- model-free/data-driven methods that learn control behavior directly from operational data.

For induction motor speed control under scalar V/f operation, fuzzy-augmented PID controllers have been demonstrated to enhance stability, reduce overshoot, and expedite response time compared with conventional PID schemes. It maintains robustness under sudden load-torque steps. In permanent magnet synchronous motor (PMSM) drives, multilayer perceptron (MLP)-based backpropagation schemes have been used to adapt PID gains online. These enhance anti-interference capability, mitigate chattering, and improve speed/trajectory tracking in systems subject to dynamic variations and uncertain disturbances. Experimental results indicate superiority over fixed-gain PID [5–7]. Collectively, these results demonstrate that incorporating learning or fuzzy logic into PID control enhances tolerance to uncertainty while maintaining low cost and a relatively simple implementation framework.

For PMSM speed control loops, optimization-based meta-heuristic algorithms have been widely applied to automate PID tuning and improve transient performance. An improved quantum genetic algorithm (IQGA) identified PID gains that yield faster and more stable responses, eliminating overshoot and oscillations across a range of operating conditions [8–10]. In traction drive studies, which were demonstrated on DC motors but are algorithmically transferable to AC drives, Dandelion Optimization-based PID (DO-PID) outperformed Particle Swarm Optimization-based PID (PSO-

PID), Firefly Algorithm-based PID (Firefly-PID), and Tabu Search-based PID (TLBO-PID) in terms of overshoot, rise/settling time, disturbance rejection, and total error [11]. Similarly, tailored PID designs in electric power steering systems have achieved better overshoot, settling time, and rise time while maintaining low computational complexity and improved adaptability [12]. In summary, optimization-based tuning improves transient metrics and disturbance rejection; however, it still inherits the structural limitations of PID when plant characteristics change significantly.

Beyond PID-centric strategies, robust controllers such as sliding mode control (SMC) have been extensively investigated. They are known to provide strong disturbance rejection, zero steady-state error, and reduced sensitivity to uncertainties compared to conventional PID implementations [2]. Fractional-order PID (FO-PID) extends PID by introducing fractional integration and differentiation orders (λ , μ), thereby improving robustness in complex, nonlinear, and time-delay systems. FO-PID has been successfully applied across domains, from servo drives to aerospace, illustrating enhanced resilience at the expense of additional parameters and tuning complexity [3, 4]. For AC drives, these methods offer significant robustness, but they can also increase design effort and, in some cases, lead to switching-related chattering or increased implementation demands.

Neural networks, particularly recurrent architectures, enable the direct learning of dynamic behaviors from time-series data. LSTM networks have been used to estimate rotor speed and load torque in induction-motor electric-vehicle scenarios. These networks maintain favorable estimation accuracy under linear and step load-torque changes, as well as in uni- and bi-directional operation. Further fine-tuning improves accuracy [13, 14]. However, performance can degrade due to variations in stator/rotor resistance, underscoring the need for robustness against parameter drift. In current prediction tasks, LSTMs have shown robustness to parameter changes and effective noise filtering, especially when trained and tested at the same high sampling frequency. However, increasing the number of LSTM cells has yielded only modest improvements in accuracy [15, 16].

Integrating an LSTM into a data-driven model predictive current control (DD-MPCC) system for synchronous machines results in a faster dynamic response than LTI-model-based controllers. The performance is comparable to that of nonlinear MPC with detailed physics models, while reducing the effort required for modeling and the amount of prior knowledge needed [17, 18].

In motor condition monitoring, LSTM outperforms classical methods, such as Support Vector Regression, in predicting single-step mechanical states (e.g., bearings). It achieves substantially higher accuracy without expert-crafted features by extracting temporal patterns directly from sensor data [19–21]. These studies demonstrate that LSTMs can capture temporal dependencies, filter noise, and reduce the modeling burden. However, they also reveal three practical caveats:

- dependence on high-quality, task-relevant data;
- sensitivity to parameter variations if not addressed during training;
- greater computational demand than fixed-gain PID.

Furthermore, much of the prior work focuses on estimation/augmentation or simulation/hybrid setups rather than replacing the control law entirely in real-time AC drives.

Although PID remains the dominant method for controlling AC motors due to its robustness and simplicity, its performance degrades in the presence of unmodeled dynamics and parameter drift. Enhanced PID (e.g., fuzzy/learning-aided or optimization-tuned), robust nonlinear control (e.g., SMC), and FO-PID have addressed some aspects of this issue by improving transient behavior, disturbance rejection, and robustness. However, these methods often increase the burden of tuning, parameterization, or implementation complexity. Many of these methods also require access to at least approximate models or rich sensing capabilities. In contrast, data-driven approaches, such as exceptionally long short-term memory (LSTM), offer a path to model-free control synthesis by learning directly from operational data. However, prior applications in motor drives have primarily focused on estimation/prediction or controller assistance rather than the complete substitution of PID in the loop.

Our approach targets AC motor speed control without requiring explicit models. First, we operate the drive with a baseline PID to collect control-relevant sequences (reference speed, measured speed, and control signals). Then, we train an LSTM to learn the mapping from historical setpoints and speed measurements to the control output. We deploy the trained LSTM as the online controller, replacing the PID in real time without requiring plant identification or reinforcement learning.

The purpose of this study is to develop and experimentally validate a practical data-driven control strategy for electric motor speed regulation in systems with unknown, nonlinear, or difficult-to-model dynamics.

Specifically, this research aims to investigate whether a Long Short-Term Memory (LSTM) neural network, trained exclusively on operational input–output data collected from a baseline PID-controlled system, can directly replace the PID controller in a closed-loop configuration without relying on explicit system identification or physics-based modeling.

The objectives of this work are threefold: 1) to design a systematic data acquisition procedure that captures control-relevant temporal patterns from a black-box motor system; 2) to construct and train an LSTM-based controller that learns the mapping from historical reference and measured speed signals to the corresponding control action; 3) to experimentally evaluate the real-time performance of the proposed LSTM controller in comparison with a conventional PID controller in terms of tracking accuracy, control smoothness, and robustness to nonlinear operating conditions.

Based on these objectives, the main contributions of this paper are as follows: first, a systematic data collection procedure was developed to extract control-relevant sequences from a black-box AC motor system operating under a baseline PID controller. Second, an LSTM-based control model was designed and trained to learn the mapping between reference setpoints, measured speed histories, and corresponding control signals. The trained LSTM network was then deployed in a closed-loop configuration to replace the conventional PID con-

troller and regulate the motor speed in real-time. Experimental validation demonstrates that the proposed LSTM controller's tracking performance is comparable to or superior to that of the PID controller across various operating conditions, and that it does not require explicit system identification.

Although Long Short-Term Memory (LSTM) networks have been extensively studied and widely applied in time-series modeling and control-related tasks, the scientific novelty of this work does not lie in the LSTM architecture itself. Instead, the novelty resides in the development and experimental validation of a practical, model-free control framework in which an LSTM network directly replaces the conventional PID controller in a closed-loop motor speed control system, without requiring explicit system identification, parameter estimation, or physics-based modeling.

Unlike most existing studies, which primarily employ neural networks to assist PID tuning, estimate system states, or serve as predictive models within hybrid control structures, the proposed approach treats the electric motor drive as a black box and learns the control law solely from operational data generated by a baseline PID controller. This direct substitution paradigm enables rapid deployment in real-world systems with unknown or highly complex dynamics, limited sensing, and strong nonlinearities, which are common in low-cost embedded motor drive applications.

Recent literature supports this perspective, indicating that scientific novelty in LSTM-based control no longer lies in the network architecture itself, but rather in how LSTM models are embedded within practical control frameworks for systems exhibiting unknown, nonlinear, or complex dynamics. Several studies have demonstrated that LSTM networks can serve as direct replacements for classical PID or PI controllers in closed-loop control systems, without requiring explicit system identification. For example, [22] reported that an LSTM-based controller can act as a drop-in substitute for a PI controller in an industrial wastewater treatment process, achieving performance comparable to or superior to that of conventional controllers while avoiding reliance on accurate mathematical models. Similar con-

cepts have also been reported in automotive and mechanical systems, where LSTM-enhanced control strategies improve robustness under parameter uncertainties and external disturbances [23, 24].

In the broader context of model-free and data-driven control, LSTM networks have proven particularly effective in capturing long-term dependencies and nonlinear dynamics that are difficult to represent using traditional control-oriented models [19, 25, 26]. Studies focusing on predictive control frameworks further illustrate that LSTM-based predictors can replace conventional plant models in Model Predictive Control (MPC), enabling stable and efficient control of ultra-supercritical power units and robotic manipulators under complex operating conditions [27–29]. These findings reflect a clear shift from analytical modeling toward learning-based dynamic representations, which provides the conceptual foundation for the novelty claimed in this work.

Methodology. The experimental framework, as illustrated in Fig. 1, is designed to develop and validate a data-driven controller for an electric motor with unknown dynamic characteristics. The methodology consists of three primary stages. Initially, a conventional PID controller is tuned and employed in a closed-loop system to regulate the motor's speed. During this phase, operational data, including the reference setpoint, measured system output, error, and the PID control signal, is collected and stored. Subsequently, this dataset is used for offline training of an LSTM neural network that learns to map the system's state history to the appropriate control signal by mimicking the PID's behavior. In the final stage, the trained LSTM model is deployed to the system, replacing the PID controller to perform real-time, online control.

To execute this workflow, a specific experimental testbed was constructed. The hardware consists of an electric fan motor managed by a PWM-based chopper driver, with a shaft encoder providing speed feedback. An Arduino Mega 2560 serves as the real-time control and acquisition unit, running the baseline PID controller via its firmware and interfacing with a host computer. The software toolkit on the host computer utilizes a Py-

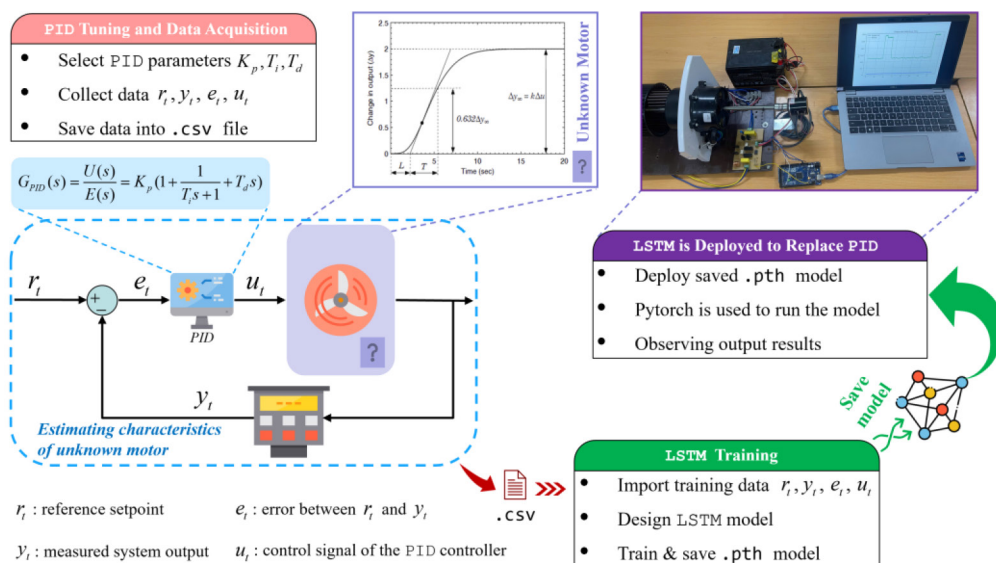


Fig. 1. An overall LSTM-based approach to replace PID control in unknown electric motor systems

thon environment for data logging and processing. The core machine learning component is built with the PyTorch framework to design, train, and validate the LSTM model before deployment for online control. This integrated setup ensures a seamless process from physical data acquisition to the final deployment and validation of the data-driven controller.

Let us consider a discrete-time control system with unknown internal dynamics. The goal is to regulate the system output $y_t \in \mathbb{R}$, such as motor speed at time step t , to follow a desired reference (or setpoint) $r_t \in \mathbb{R}$ by generating an appropriate control input $u_t \in \mathbb{R}$, typically represented as a PWM duty cycle.

Rather than designing a controller based on an identified plant model, we propose a data-driven approach using a Long Short-Term Memory (LSTM) network trained to adapt the behavior of the electric motor system. Our goal is to replace an existing PID controller with an LSTM-based model. Table 1 describes our approach in detail.

Data collection and problem formulation. The system is first operated under a traditional PID controller, during which the relevant signals are recorded at each time step t . Specifically, the reference setpoint r_t (in RPM), the measured system output y_t (in RPM), and the control signal u_t generated by the PID controller (scaled to 0–100 %) are collected for subsequent analysis.

Each sample at time t is represented as a tuple $x_t = [r_t, y_t, u_t] \in \mathbb{R}^3$. We collect a dataset of such samples over T time steps, where $\mathcal{D} = \{x_1, x_2, \dots, x_T\}$.

To incorporate temporal information, we use a fixed-length sliding window of size $k + 1$, and construct sequences of input-output pairs for supervised learning. Each input sequence is defined as $X_t = [r_{t-k}, y_{t-k}, r_t, y_t] \in \mathbb{R}^{2(k+1)}$ and the target output is

$$\hat{u}_t = f_0(X_t) \approx u_t,$$

where F_0 is the LSTM-based control function parameterized by learnable weight θ , and $\hat{u}_t$ is the predicted control signal.

Model architecture. The LSTM model is designed to approximate the mapping $f_0: \mathbb{R}^{(k+1) \times 2} \rightarrow \mathbb{R}$. It consists of:

1. An input layer that receives the sequence X_t , reshaped as a matrix with shape $(k + 1) \times 2$, corresponding to the setpoint and measured output at each time step.

2. LSTM layers that model the temporal relationships in the data

$$h_t = \text{LSTM}(X_t),$$

where $h_t \in \mathbb{R}^d$ is the hidden state vector at the final LSTM time step.

A fully connected output layer that maps h_t to the scalar output as follows

$$\hat{u}_t = W \cdot h_t + b.$$

With $W \in \mathbb{R}^{1 \times d}$ and $b \in \mathbb{R}$ as trainable parameters.

Training procedure. The model is trained to minimize the mean squared error (MSE) between the predicted output $\hat{u}_t$ and the actual control signal u_t

$$\mathcal{L}(\theta) = \frac{1}{N} \sum_{t=1}^N (\hat{u}_t - u_t)^2,$$

where N is the total number of training samples.

The loss is minimized using stochastic gradient descent with the Adam optimizer. Input sequences are normalized using the training set mean and standard deviation to ensure stable convergence.

Online deployment. After training, the LSTM model is deployed as a real-time controller. At each time step t , the system collects the most recent sequence of (r, y) pairs, forms X_t , and uses the model to compute the control signal as follows

$$u_t \leftarrow f_0(r_{t-k:t}, y_{t-k:t}).$$

The computed control output u_t is then sent as the PWM command to the motor driver.

Experimental setup. The physical system employed in this study consists of an electric fan motor driven by a PWM-based chopper driver, an encoder for measuring shaft speed, and an Arduino Mega 2560 microcontroller, which is responsible for signal acquisition and real-time control. A PID controller is implemented within the Arduino firmware to regulate system behavior, while a host computer is utilized for data logging and subsequent training of the LSTM model.

Data acquisition. During operation under PID control with parameters $K_p = 2.0$, $K_i = 0.5$ and $K_d = 0.01$, the system records the triplet $x_t = [r_t, y_t, u_t]$ where r_t is the setpoint, y_t is the measured output, and u_t is the PID output in percent PWM.

The dataset contains $T = 3,000$ samples, collected at a sampling rate of 100 Hz. The reference signal r_t changes every 2–4 seconds to simulate realistic variations.

Data preprocessing. All signals are normalized to zero mean and unit variance. A sliding window of $k = 10$ previous time steps is used to create input sequences

$$X_t = [r_{t-k}, y_{t-k}, r_t, y_t] \in \mathbb{R}^{2(k+1)}.$$

With the target output u_t at time t .

The dataset is split into 80 % training and 20 % testing data, preserving sequence order to maintain temporal consistency.

Table 1

Roles of hardware components in each stage of the experimental workflow

Stage	Hardware involved	Description
1. Motor characterization	Arduino + Drvie + Encoder	A fixed PWM control signal is applied to the motor, and the resulting speed is measured to estimate the motor characteristics
2. PID Tuning	Arduino + Drvie + Encoder + PID	PID parameters are determined based on the motor characteristics and then used for reference tracking of motor speed
3. Data Acquisition		At each time step, the reference speed r_t , measured speed y_t , and control signal u_t are recorded
4. LSTM Training and Deployment	Arduino + Drvie + Encoder + LSTM	The collected data is used to train an LSTM model. After training, the model generates control signals to replace the PID controller

Model configuration. The LSTM architecture designed for this study comprises an input layer that receives a $(k + 1) \times 2$ sequence of the reference setpoint and the system output, followed by a single LSTM layer with 64 hidden units and a tanh activation function. To mitigate overfitting, a dropout layer with a 20 % dropout rate is included. Finally, a dense layer with a linear activation function produces the predicted control signal $\hat{u}_t$.

The model is trained using the Adam optimizer with a learning rate of 0.001 and a batch size of 64. The Mean Squared Error (MSE) is employed as the loss function, while early stopping with a patience of 10 epochs is applied to prevent overfitting. Under these settings, training typically converges after 40–60 epochs.

Evaluation metrics. To evaluate the performance of the proposed approach, two primary metrics are used. The first is the Mean Absolute Error (MAE), defined as

$$MAE = \frac{1}{N} \sum_{t=1}^N |\hat{u}_t - u_t|,$$

which measures the average deviation between the predicted control signal $\hat{u}_t$ and the actual control signal u_t .

The second metric is the tracking error, calculated as the mean absolute difference between the measured system output y_t and the reference setpoint y_r during the online phase.

Results and discussion. Estimate motor characteristics. As shown in Figs. 2 and 3, the motor characteristics are determined through an open-loop experiment with a PID controller, where the input signal is changed approximately every 5 seconds. It achieves a maximum velocity of 2,905.8 RPM and stabilizes at a final velocity of 2,865.72 RPM, with a rapid rise time of 0.205 seconds.

The static gain of 37.1 % reflects good sensitivity to control inputs, although the high average control signal (77.25 %) and frequent saturation at 100 % suggest significant control effort. A low average delay of 0.102 sec-

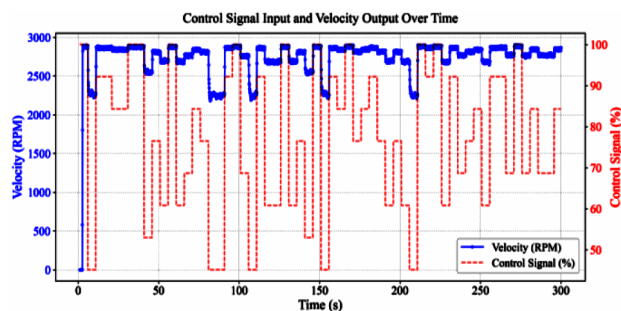


Fig. 2. Experimental results of the motor with open-loop control

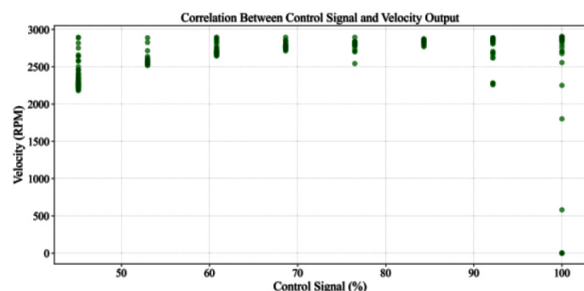


Fig. 3. Correlation between control signal and velocity

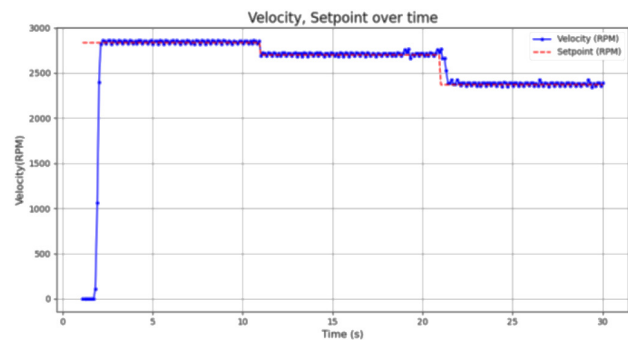


Fig. 4. Results of the motor with PID closed-loop control

onds (range: 0.089–0.115 s) confirms high responsiveness. The moderate overall correlation (0.477) between the control signal and velocity, contrasted with stronger cycle-specific correlations (0.85–0.93 in many 5-second cycles), suggests nonlinearities, likely due to saturation or mechanical factors.

As illustrated in Fig. 4, the motor operating under a closed-loop PID controller exhibits distinct responses across three cycles of setpoint changes.

In Cycle 1 (1.11–11.01 s), the motor velocity reaches 2,598.85 RPM against a setpoint of 2,936 RPM, resulting in a 337.15 RPM error and a 100 % PID output, indicating controller saturation. During Cycle 2 (11.01–21.02 s), the measured velocity of 2,691.36 RPM closely follows the setpoint of 2,700 RPM, with an error of only 8.64 RPM and a corresponding PID output of 68.35 %. In Cycle 3 (21.02–30.01 s), the output velocity rises to 2,390.75 RPM, slightly overshooting the setpoint of 2,370 RPM by 20.75 RPM, with a PID output of 50.96 %. The observed positive correlation (0.672) between control effort and velocity response demonstrates improved linearity of the system.

The statistics of the experimental results for the motor with PID closed-loop control are listed in Table 2.

Fig. 5 and Table 3 present the results of motor control using both PID and LSTM over a 300-second duration, with 2,993 recorded samples. Both controllers exhibit high control effort, with mean values of 83.10 % for the PID and 80.95 % for the LSTM, and frequent saturation at 100 %. Due to the system's nonlinear nature, overall correlations remain relatively low. The motor exhibits a fast dynamic response, characterized by a rise time of 0.20 s and a delay of 0.107 s.

The PID controller exhibits a simple and rapid response, with a rise time of 0.20 seconds and a delay of 0.107 seconds. It performs effectively at stable setpoints, maintaining outputs in the range of approximately 68.64–100 % during cycles of 11.10–151.70 seconds. However, frequent saturation at 100 % (e.g., in the intervals 1.00–6.00 and 25.99–150.91 s) reduces control pre-

Table 2

Descriptive statistics of PID data

Attribute	Mean	Std.Dev.	Min	Max
Time, s	15.5	8.3	1.1	30
Setpoint, rpm	2,677.0	229.87	2,370.0	2,936.0
Velocity, rpm	2,565.1	476.89	45.21	2,860.7
Output, %	73.7	29.4	0.04	100.0
Error, rpm	111.8	488.2	–293.6	2,890.7

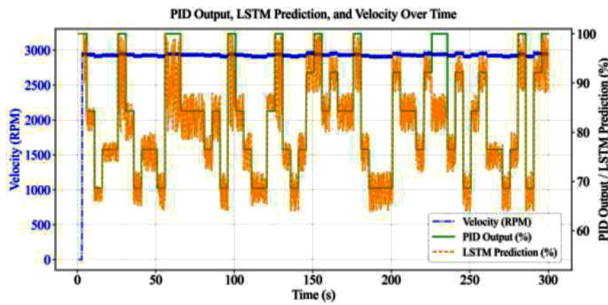


Fig. 5. Visualization of motor velocity controlled by PID and LSTM

Table 3

Descriptive statistics of motor data

Attribute	Mean	Std.Dev.	Min	Max
Time, s	15.5	8.3	1.1	30
Setpoint, rpm	2,677.0	229.87	2,370.0	2,936.0
PID Output, %	2,565.1	476.89	45.21	2,860.7
LSTM prediction, %	73.7	29.4	0.04	100.0

cision. Furthermore, the low correlation (-0.078) between control effort and velocity response, along with constant output values, leads to oscillations in variable velocity cycles (2,890–2,990 RPM).

The LSTM controller produces smoother control outputs, with a standard deviation of 9.68 compared to 11.06 for PID, and a slightly lower mean output level (80.95 % vs. 83.10 %). It also achieves a higher correlation in certain intervals, such as 0.995 in the cycle between 13.50 and 13.80 s, indicating improved alignment between the control effort and velocity response. Nevertheless, the approach involves a more complex implementation, and the correlation across cycles remains inconsistent.

Fig. 6 shows our experimental setup, in which the LSTM model is deployed in real time at 10 Hz on the embedded platform. It generates stable and smooth control outputs, as shown in Fig. 7. The system effectively tracks changing setpoints, confirming the feasibility of using the trained LSTM model as a replacement for the PID controller.

Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), are capable of retaining information over extended time horizons, making them more effective at handling time-series data than traditional controllers such as PID controllers. Replacing a PID controller with an LSTM can offer several advantages.

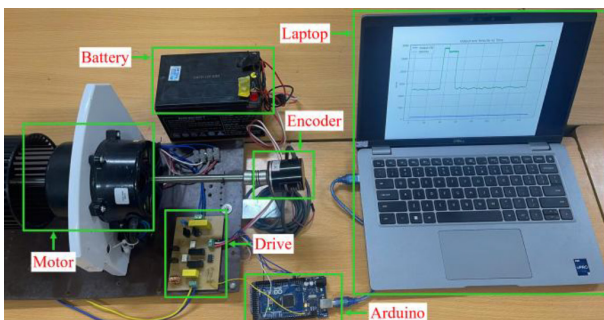


Fig. 6. Experimental setup

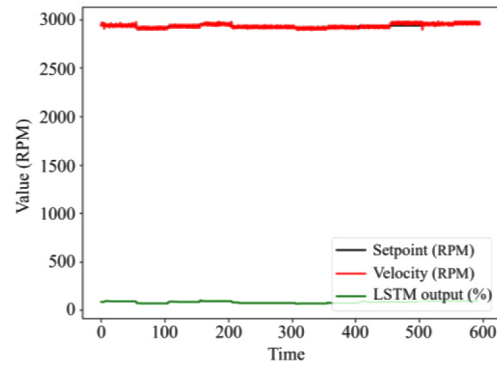


Fig. 7. Experimental results

1. While PID is a linear controller that relies on manually tuned parameters (K_p , K_i , K_d) or heuristic optimization methods such as Ziegler–Nichols, LSTM learns directly from historical data. It can automatically discover relationships between inputs (control signals, system states) and outputs (speed, position, force) without predefined rules. As a result, LSTM often outperforms PID when the system is highly nonlinear or time-variant.

PID reacts only to the current error, adjusting its output based solely on the difference between the measured value and the setpoint (feedback control). In contrast, LSTM has predictive capabilities, enabling proactive control by anticipating fluctuations and adjusting earlier. This reduces error and enhances overall stability.

PID performance deteriorates in the presence of significant time delays, often leading to oscillations or instability, since it reacts only to the current error. LSTM, however, learns temporal dependencies between past and present data, allowing it to compensate for delays and make more accurate predictions.

LSTM is particularly advantageous in systems with long delays or strong nonlinearities. Nevertheless, certain limitations remain where PID may still be preferable. Specifically, LSTM requires high-quality training data; with insufficient or non-representative datasets, model performance may degrade. Moreover, while PID provides fixed parameters that ensure stability, LSTM does not guarantee absolute stability and may exhibit high variance if not adequately trained. Finally, LSTM is computationally more demanding, whereas PID is simpler and faster.

In general, PID controllers remain the preferred option for simple, stable systems that require low computational effort. However, when dealing with nonlinear dynamics, significant delays, or the need for adaptive control, LSTM-based controllers provide superior performance. A detailed comparison of the two approaches is presented in Table 4.

As shown in Table 4, PID controllers are simple, computationally efficient, and provide straightforward stability control, making them well-suited for simple, well-characterized systems. However, their limited adaptability, poor handling of nonlinearities, and inability to manage time delays restrict their performance in complex environments. By contrast, LSTM controllers excel at learning from data, adapting automatically, and providing predictive capabilities, enabling superior performance under nonlinear and time-delayed conditions. These benefits, however, come at the cost of high-

Table 4

Descriptive statistics of motor data

Features	PID	LSTM
Learning capability	Requires manual tuning	Learns from data
Nonlinearity handling	Poor	Good
Time delay handling	Poor	Good
Predictive capability	No	Yes
Adaptability	Requires re-tuning	Automatically adapts
Computational load	Low	High
Stability	Easily controllable	Needs careful design

er computational requirements and the need for careful design to ensure stability.

Conclusion. This study demonstrates the feasibility of employing a data-driven LSTM network as a direct replacement for a conventional PID controller in regulating the speed of electric motors with unknown dynamic characteristics. The key scientific contribution is that an LSTM-based controller trained exclusively on operational data from a PID-regulated system can achieve stable, real-time control without requiring an explicit mathematical model of the plant.

Experimental evaluations confirmed that, while the baseline PID controller maintained overall stability, its performance was constrained by frequent signal saturation and weak correlation with actual motor velocity, reflecting its limitations in capturing nonlinear motor dynamics. In contrast, the LSTM controller generated smoother control signals and achieved stronger correlations in specific operating cycles, thereby offering superior performance in handling system nonlinearities.

The paper, moreover, explicitly addresses the complete replacement of the control logic in electric motor drives. By treating the motor system as a “black box”, the study addresses the limitations of classical PID, such as sensitivity to parameter drift and signal saturation. The experimental validation confirms that the LSTM controller achieves comparable or superior tracking performance and smoother control signals in nonlinear regimes compared to a baseline PID, all without the computational burden of real-time model identification.

From a practical standpoint, the proposed approach is highly relevant in scenarios where system identification is impractical, unreliable, or prohibitively expensive, conditions often encountered in low-cost embedded platforms and complex industrial machinery. By learning control policies directly from data, the need for extensive modeling is reduced, enabling the design of adaptive controllers deployable on resource-constrained platforms. Consequently, this approach holds significant promise for advancing automation in robotics, process control, and other industrial domains where adaptability and robustness are essential.

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Керування електродвигунами невідомої моделі на основі даних LSTM для заміни PID-регулятора

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Мета. Розробити та протестувати стратегію керування на основі даних, що передбачає заміну традиційного пропорційно-інтегрально-диференційного (PID) регулятора нейронною мережею із довгою короткочасною пам'яттю (LSTM) для регулювання швидкості електродвигуна в системах із невідомою або складною динамікою.

Методика. Запропонований підхід складається із трьох основних етапів: 1) робота електродвигуна під керуванням базового PID-регулятора та збір експлуатаційних даних (задані значення, виміряні швидкості й керувальні сигнали); 2) навчання мережі LSTM для апроксимації відображення між історією заданих значень, виміряними вихідними сигналами й відповідними керувальними діями, сформованими PID-регулятором; 3) упровадження навченої LSTM-моделі в режимі реального часу як прямого регулятора. Експериментальне тестування виконане на вбудованому випробувальному стенді, що включає вентиляторний електродвигун, драйвер широтно-імпульсної модуляції (PWM), енкодер і контролер Arduino Mega 2560, при цьому модель LSTM навчалася у середовищі PyTorch і виконувалася в режимі онлайн.

Результати. Регулятор на основі LSTM забезпечує успішне відстеження змінних заданих значень і формує більш плавні сигнали керування порівняно із базовим PID-регулятором. Досягнуто схожої або нижчої усталеної похибки, а також вищої кореляції між рівнем контролю та швидкістю руху електродвигуна, при одночасному зменшенні коливань у нелінійних режимах роботи.

Наукова новизна. На відміну від більшості попередніх досліджень, де нейронні мережі використовуються для налаштування PID-регуляторів або оцінювання стану системи, у цій роботі продемонстроване їх пряме заміщення LSTM-регулятором, навчання якого здійснюється виключно на основі експлуатаційних даних без необхідності явної ідентифікації системи чи фізико-математичного моделювання.

Практична значимість. Запропонований підхід є ефективним рішенням для керування електродвигунами в умовах, коли ідентифікація системи є неможливою, ненадійною або економічно нецільною. Метод є особливо актуальним для низьковартісних вбудованих платформ і промислових застосувань, що потребують адаптивних стратегій керування на основі даних, здатних урахувати нелінійності й часові затримки.

Ключові слова: LSTM, заміна PID-регулятора, моделювання часових рядів, регулювання швидкості електродвигуна

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