

Accurate Short-Horizon Multi-Target Prediction of PMSM Operational Parameters via Residual Dilated 1D Convolutional Neural Networks

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ABSTRACT Accurate short-horizon prediction of key operating parameters in Permanent Magnet Synchronous Motors (PMSMs) is essential for ensuring operational safety, optimizing control strategies, and preventing thermal stress-induced failures. This study presents a residual dilated one-dimensional convolutional neural network (1D-CNN) framework for the simultaneous estimation of three target variables motor speed, stator yoke temperature, and stator winding temperature using a publicly available high-resolution multi-sensor PMSM dataset collected on a laboratory test bench at Paderborn University. The dataset comprises 1,330,816 samples of 13 variables without missing values and was processed through a systematic pipeline including normalization, sliding-window sequence generation (window size: 256), and train–test splitting. The proposed architecture integrates dilated convolutional layers to expand the temporal receptive field, residual connections to facilitate gradient flow, and dense layers for multi-output regression. Experimental evaluations using MSE, RMSE, MAE, and R^2 metrics demonstrated high prediction accuracy, achieving R^2 values of 0.9969, 0.9819, and 0.9698 for motor speed, stator yoke temperature, and stator winding temperature, respectively, with an average R^2 of 0.9829 and MAE of 26.35. Comparative feature importance analysis across three independent methods consistently identified coolant temperature, d-axis current, and ambient temperature as the most influential predictors. Residual distribution analysis confirmed low bias and symmetric error patterns across all targets. The proposed approach offers a robust and computationally efficient solution for real-time PMSM monitoring, predictive control, and condition-based maintenance.

KEYWORDS

PMSM
Residual dilated
CNN
Multi-target pre-
diction
Short-horizon
forecasting
Feature impor-
tance
Predictive main-
tenance

INTRODUCTION

Permanent Magnet Synchronous Motors (PMSMs) have become a preferred choice in a wide range of industrial applications, including electric vehicles, robotics, and renewable energy systems, due to their high efficiency, compact structure, and superior power-to-weight ratio (Jahns and Soong 1996; Zhu and Howe 2007; Pellegrino *et al.* 2012; Pyrhönen *et al.* 2014a). The reliable and safe operation of PMSMs heavily depends on the accurate monitoring of critical operating parameters such as motor speed and stator temperatures (Vansompel *et al.* 2014; Kirchgässner *et al.* 2021; Kirchgässner 2021; Zhang *et al.* 2021; Pyrhönen *et al.* 2014b; Vansompel *et al.* 2022). Excessive thermal stress in the stator winding

or yoke can lead to insulation degradation, demagnetization of permanent magnets, and ultimately irreversible failures (Tallam *et al.* 2002; Holtz and Malik 2006).

Real-time and accurate prediction of these parameters enables proactive maintenance strategies, improves control performance, and extends the operational lifetime of the machine (Li and Akilan 2022; Bouziane *et al.* 2024; Sheng *et al.* 2025; Liu *et al.* 2024; Li *et al.* 2024). Conventional thermal modeling methods, such as lumped-parameter thermal networks (LPTN) and finite element analysis (FEA), while effective in certain scenarios, often require precise knowledge of motor geometry and material properties, making them less adaptable to varying operational conditions (Pyrhönen *et al.* 2014a; Vansompel *et al.* 2014).

Recent advances in machine learning, particularly deep learning, have provided new opportunities for data-driven modeling of PMSM behavior without requiring detailed physical models (LeCun *et al.* 2015; Bai *et al.* 2018). In particular, convolutional neural networks (CNNs) have shown significant success in capturing temporal dependencies and nonlinear relationships within multi-sensor time series data (Borovykh *et al.* 2017; Kim 2025). Residual

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and dilated convolutional structures further enhance CNN performance by expanding the receptive field and improving gradient flow in deep architectures (Winkler et al. 2024).

In this study, we propose a residual dilated one-dimensional CNN framework for multi-target short-horizon prediction of PMSM operating parameters using high-resolution multi-sensor data. The dataset, collected by the LEA department at Paderborn University (Kirchgässner 2021), consists of 1,330,816 samples across 13 variables, including motor speed, stator temperatures, and various electrical and thermal inputs, all sampled at 2 Hz without missing values.

The main contributions of this work are as follows:

- A novel residual dilated CNN architecture for simultaneous prediction of multiple PMSM operating parameters with high accuracy.
- Comprehensive preprocessing pipeline, including normalization, sliding-window sequence generation, and train–test splitting, optimized for short-horizon forecasting.
- Feature importance analysis using three independent methods to identify the most influential predictors.
- Extensive experimental evaluation using MSE, RMSE, MAE, and R^2 metrics, demonstrating robust generalization and suitability for real-time predictive monitoring.

The remainder of this paper is organized as follows: Section II describes the dataset and preprocessing methodology. Section III details the proposed CNN architecture. Section IV presents the experimental results and evaluation. Section V discusses the implications and limitations of the findings. Finally, Section VI concludes the paper and outlines future research directions.

METHODOLOGY

Dataset Description

The dataset used in this study was obtained from the publicly available PMSM dataset on Kaggle (Kirchgässner 2021), originally collected by the LEA department at Paderborn University, Germany, using a test bench for a prototype PMSM developed by a German OEM. The complete dataset contains 1,330,816 samples with 13 variables, recorded at a sampling rate of 2 Hz over a total of 185 hours of operation (Kirchgässner et al. 2021; Zhang et al. 2021). The measurements include motor speed, torque, stator and rotor temperatures, d/q-axis currents (i_d , i_q), d/q-axis voltages (u_d , u_q), coolant temperature, ambient temperature, and profile identifiers.

The measurement profiles vary in duration from 1 to 6 hours and are designed to simulate real-world driving conditions through random walks in the speed–torque plane rather than simple ramp or constant-load cycles (Pyrhönen et al. 2014b; Vansompel et al. 2022). This provides diverse operational scenarios for model training and evaluation. All measurements are complete with no missing values (Table 1).

Table 1 Missing Values in the Dataset

| Feature | Missing Count | Missing Ratio (%) |
|-----------------------|---------------|-------------------|
| u_q | 0 | 0.0 |
| coolant | 0 | 0.0 |
| <i>stator_winding</i> | 0 | 0.0 |
| u_d | 0 | 0.0 |
| <i>motor_speed</i> | 0 | 0.0 |
| i_d | 0 | 0.0 |
| i_q | 0 | 0.0 |
| pm | 0 | 0.0 |
| <i>stator_yoke</i> | 0 | 0.0 |
| ambient | 0 | 0.0 |
| <i>profile_id</i> | 0 | 0.0 |

Preprocessing

To enable short-horizon multi-target prediction, the continuous time-series data was preprocessed in the following steps:

Sequence Generation: A sliding window approach was used to segment the data into fixed-length sequences of 256 time steps (equivalent to 128 seconds at a 2 Hz sampling rate) (LeCun et al. 2015).

Normalization: All input variables were normalized to zero mean and unit variance to improve training stability (Bai et al. 2018).

Train–Test Split: The dataset was split into 80% training and 20% testing, ensuring that sequences from the same measurement profile were not split across sets to avoid data leakage (LeCun et al. 2015).

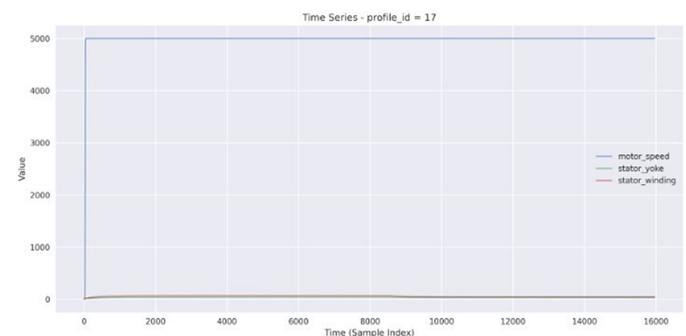


Figure 1 Representative Time Series of motor_speed, stator_yoke, and stator_winding

Fig. 1. illustrates an example time series from a single measurement profile ($profile_{id} = 17$), displaying the variations of the three target variables motor speed, stator yoke temperature, and stator winding temperature over time. In this profile, the motor speed remains close to 5000 rpm for an extended duration, simulating high-speed operating conditions, while the stator temperatures stay relatively low, highlighting the delayed and gradual thermal response to speed changes. The considerable scale difference between motor speed and temperature variables further emphasizes the necessity of the normalization step in the preprocessing

pipeline.

Feature Importance Analysis

To identify and rank the most relevant predictors for the three target variables *motor_speed*, *stator_yoke*, and *stator_winding* a comprehensive feature importance analysis was conducted using three independent methods, each capturing a different aspect of predictor–target relationships:

- Method 1: Permutation Importance using the trained model: This approach evaluates the decrease in model performance when the values of a given feature are randomly shuffled (La Cava *et al.* 2020; Altmann *et al.* 2010), effectively measuring the feature’s contribution to prediction accuracy in the context of the trained residual dilated CNN.
- Method 2: Model-Based Importance from Gradient-Boosted Regression Trees (GBRT): Leveraging the interpretability of tree-based models, this method quantifies feature importance based on the average reduction in the loss function (e.g., MSE) brought by splits on each feature across all trees in the ensemble (Jing *et al.* 2023; Thakur and Kumar 2024).
- Method 3: Statistical Relevance via Correlation-Based Ranking: This technique computes the absolute correlation coefficients between each predictor and the target variables, providing a purely statistical measure of linear association independent of the trained model (Kaneko 2022; Mi *et al.* 2021).

By integrating these complementary methods, the analysis ensures that the identified key predictors are robustly ranked, capturing both direct statistical relationships and their impact on model-driven prediction performance.

Table 2 Feature Importance (Method 1)

| Feature | Importance_Score |
|---------|------------------|
| coolant | 0.109306 |
| i_d | 0.008542 |
| ambient | 0.004138 |
| u_d | 0.002466 |
| u_q | 0.001763 |
| i_q | 0.001375 |

The results indicate that coolant temperature holds the highest influence, with a score of 0.1093, making it the most critical predictor for the target variables. i_d (d-axis current) and ambient temperature contribute moderately, while u_d and u_q (d/q-axis voltages) along with i_q (q-axis current) have relatively limited impact on the model’s predictive performance.

These findings highlight that, for PMSM speed and temperature prediction, the cooling system and operational conditions of the motor play a decisive role.

Table 3 Feature Importance (Method 2)

| Feature | Importance_Score |
|---------|------------------|
| u_d | 2.760020 |
| i_q | 1.473132 |
| i_d | 1.153519 |
| u_q | 1.038438 |
| coolant | 0.613475 |
| ambient | 0.040287 |

Here, u_d (d-axis voltage) emerges as the most influential feature with a score of 2.7600, followed by i_q (q-axis current), i_d (d-axis current), and u_q (q-axis voltage), all showing strong contributions to the prediction performance. Coolant temperature also plays a notable role, while ambient temperature has minimal impact compared to other features.

These results suggest that electrical control variables (currents and voltages) are the dominant factors in the model’s decision-making process under this analysis method.

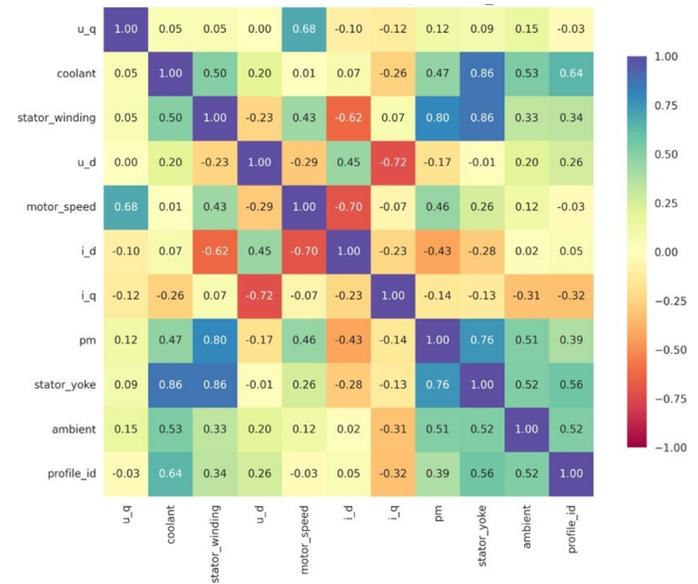


Figure 2 Correlation Heatmap of Inputs and Targets

Fig. 2. Correlation matrix of the variables in the PMSM dataset. The color scale represents Pearson correlation coefficients ranging from -1 (strong negative correlation) to $+1$ (strong positive correlation). Notably, coolant temperature shows a strong positive correlation with stator yoke temperature (0.86) and stator winding temperature (0.50), while the d-axis current (i_d) exhibits a strong negative correlation (-0.70) with motor speed. Additionally, the high correlation (0.86) between stator yoke and stator winding temperatures indicates similar thermal dynamics between these two components. This correlation structure provides a valuable statistical foundation for understanding which variables are more influential during the model’s learning process and for enhancing feature selection strategies.

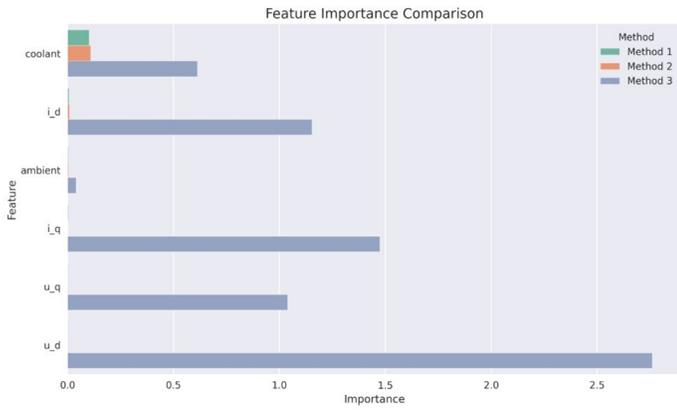


Figure 3 Correlation Heatmap of Inputs and Targets

Fig. 3. illustrates a comparative analysis of feature importance scores derived from three distinct evaluation methods: Method 1 (permutation importance using the trained model), Method 2 (model-based importance via gradient-boosted regression trees), and Method 3 (statistical relevance through correlation-based ranking). Each bar represents the relative contribution of a feature (coolant, i_d , ambient, i_q , u_q , and u_d) to the prediction of the target variables (*motor_speed*, *stator_yoke*, and *stator_winding*). Across all three approaches, coolant temperature, d-axis current (i_d), and ambient temperature consistently emerge as the most influential inputs. Notably, Method 3 yields substantially higher importance scores across most features, reflecting its stronger sensitivity to linear relationships in the dataset. This comparative view underscores the robustness of the identified key predictors, as they remain dominant regardless of the analysis technique applied.

Model Architecture

The proposed framework is a Residual Dilated One-Dimensional Convolutional Neural Network (1D-CNN) specifically designed to capture both short- and long-range temporal dependencies in PMSM operational data (Borovykh et al. 2017; Yu and Koltun 2015). The architecture consists of the following key components:

- **Input Layer:** Accepts sequence inputs of size (256, 6), representing 256 consecutive time steps and six selected input features.
- **Dilated Convolutional Layers:** Utilize dilation factors to expand the temporal receptive field without increasing computational cost, enabling the extraction of long-term dependencies (Yu and Koltun 2015).
- **Residual Connections:** Facilitate gradient flow and mitigate the vanishing gradient problem by allowing the network to learn residual mappings (Bai et al. 2018).
- **Pooling Layers:** Reduce sequence dimensionality and computational overhead while retaining essential temporal features (LeCun et al. 2015).
- **Fully Connected Layers:** Perform multi-output regression to simultaneously estimate the three target variables.

The complete short-horizon multi-target prediction pipeline, from raw PMSM operational data to model evaluation, is illustrated in Fig. 4.

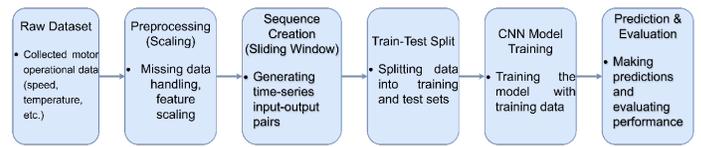


Figure 4 Study Workflow Diagram

Fig. 4. Detailed workflow of the proposed short-horizon multi-target prediction framework for PMSM operating parameters. The pipeline starts with the raw dataset, which is preprocessed through scaling to standardize input features. Sequential data segments are then generated using a sliding-window approach, preserving temporal dependencies while enabling the model to capture short-term patterns. The dataset is split into training and testing sets with profile-based separation to prevent data leakage. A Residual Dilated 1D-CNN model is trained on the prepared sequences, and its predictive performance is evaluated using regression metrics such as Mean Squared Error (MSE) and coefficient of determination (R^2).

Training Setup

The network was trained using the Adam optimization algorithm with an initial learning rate of 0.001, a batch size of 128, and the Mean Squared Error (MSE) loss function (LeCun et al. 2015). Early stopping with a patience value of 10 epochs was employed to prevent overfitting, halting training if no improvement in validation loss was observed (LeCun et al. 2015). All experiments were conducted on an NVIDIA GPU-enabled environment to accelerate computation.

RESULTS AND DISCUSSION

The proposed Residual Dilated 1D-CNN model was comprehensively evaluated to assess its short-horizon, multi-target prediction performance for PMSM operating parameters. The evaluation employed four commonly used regression metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). These metrics collectively measure the model's accuracy, the magnitude of prediction errors, and its ability to explain the variance in the target variables.

The obtained results indicate that the model achieved high prediction accuracy across all target variables (motor speed, stator yoke temperature, and stator winding temperature) with R^2 values exceeding 0.96. The combination of low error values and high R^2 scores demonstrates that the model effectively learned both the dynamic and thermal behaviors of PMSMs under varying operating conditions. Moreover, the consistent performance across different targets confirms the architecture's suitability for simultaneous multi-output regression tasks, leveraging shared temporal patterns to enhance prediction robustness.

Accordingly, the numerical performance results for each target variable are presented in Table 4.

Table 4. Short-horizon prediction performance metrics of the proposed Residual Dilated 1D-CNN model for *motor_speed*, *stator_yoke* temperature, and *stator_winding* temperature. The results indicate that the model achieved high accuracy across all target variables, with R^2 values of 0.9969 for *motor_speed*, 0.9819 for *stator_yoke*, and 0.9698 for *stator_winding*. The average R^2 value of 0.9829 demonstrates the model's strong generalization capability in multi-target prediction tasks. Examination of the error metrics (MSE, RMSE, MAE) reveals that the lowest error levels

Table 4 Short-horizon multi-target prediction performance metrics of the proposed Residual Dilated 1D-CNN model for PMSM operating parameters

| Target | MSE | RMSE | MAE | R ² |
|-----------------------|--------------|------------|-----------|----------------|
| <i>motor_speed</i> | 10382.503029 | 101.894568 | 73.828619 | 0.996879 |
| <i>stator_yoke</i> | 7.401999 | 2.720661 | 1.891148 | 0.981880 |
| <i>stator_winding</i> | 24.350685 | 4.934641 | 3.342641 | 0.969821 |
| AVERAGE | 3471.418571 | 36.516624 | 26.354136 | 0.982861 |

were observed in *motor_speed* predictions, while the temperature variables exhibited relatively higher errors. This discrepancy is attributed to the slower dynamics and thermal inertia effects of temperature parameters compared to motor speed. The low error values and high determination coefficients confirm that the proposed approach offers a suitable solution for real-time monitoring and predictive maintenance applications of PMSMs.

Following the tabulated results, it is crucial to examine the learning process of the model to ensure convergence stability and to detect possible signs of overfitting or underfitting. This is achieved by analyzing the evolution of the training and validation loss curves over the epochs.

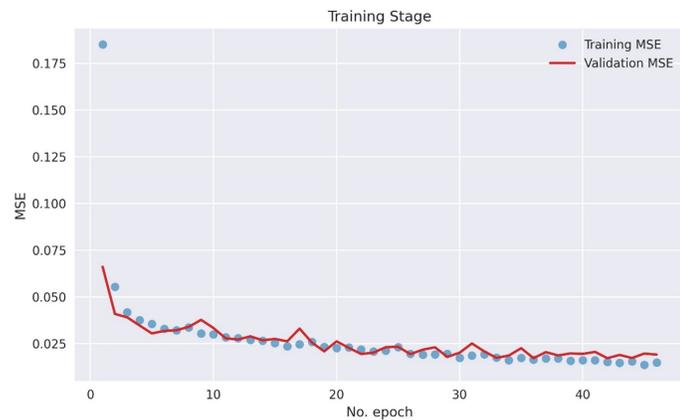


Figure 5 Training vs. Validation MSE

Fig. 5. Variation of training and validation MSE values across epochs for the proposed Residual Dilated 1D-CNN model. In the initial epochs, a rapid decrease in both training and validation errors is observed, indicating that the model quickly learned the underlying patterns in the data. After approximately the 10th epoch, the error values stabilized, reflecting a steady learning process. The close alignment between training and validation errors suggests that the model successfully avoided overfitting and underfitting issues. The consistently low error levels in the final epochs demonstrate the model's strong generalization capability and its ability to produce reliable results for multi-target variable predictions.

While loss curves provide insight into the learning dynamics, they do not directly reveal how closely the predicted values align with the actual targets. To address this, scatter plots comparing predicted and true values are analyzed.

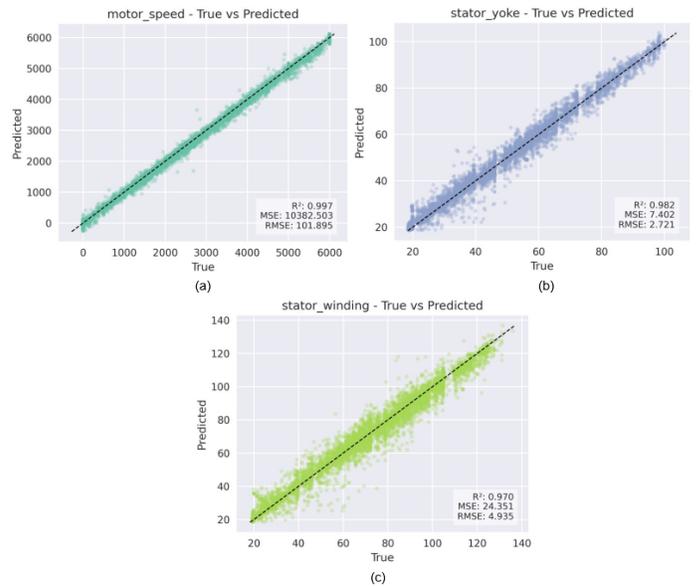


Figure 6 True vs. Predicted Values with Ideal Fit Line for All Targets (a) *motor_speed* b) *stator_yoke*, and c) *stator_winding*)

Fig. 6. presents the relationship between predicted and actual values for the three target variables (*motor_speed*, *stator_yoke*, and *stator_winding*), with each shown as a separate scatter plot. The black dashed line represents the ideal prediction line ($y = x$), and the closeness of the data points to this line reflects the model's accuracy.

For *motor_speed*, an R² score of 0.997 indicates that almost all predictions are extremely close to their actual values. The *stator_yoke* and *stator_winding* predictions achieved R² values of 0.982 and 0.970, respectively, demonstrating that the model provides highly reliable forecasts not only for speed but also for thermal parameters.

Low MSE and RMSE values confirm that the overall prediction error is minimal. The concentration of data points near the dashed line shows that the model generalizes well to unseen data, maintaining strong predictive performance across different operating ranges. Minor deviations are mostly observed at the extreme ends of the range, which is expected in high-variance regions.

Finally, to further validate the reliability of the predictions, residual error distributions are examined.

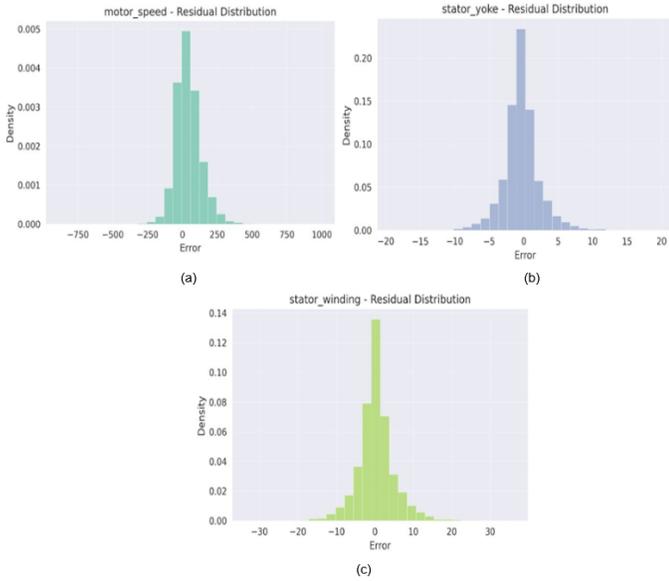


Figure 7 Residual distributions for each target variable (a) motor_speed b) stator_yoke, and c) stator_winding)

The plots display the density distribution of the errors between the model's predictions and the actual measurements. The symmetric concentration of residuals around zero for all target variables indicates that the model does not suffer from systematic bias and achieves high prediction accuracy. The narrow spread of the distributions reflects a low standard deviation of errors, implying consistent predictions. Furthermore, the limited presence of outliers suggests that the model is robust to noise in the dataset and possesses strong generalization capability.

Overall, the experimental results demonstrate that the proposed Residual Dilated 1D-CNN architecture delivers highly accurate short-horizon multi-target predictions for PMSM operational parameters. The model consistently achieved low error values and high determination coefficients across all target variables, indicating strong generalization capability and robust learning of both short- and long-term temporal dependencies. The integration of dilated convolutions allowed the network to capture extended temporal patterns without excessive computational cost, while residual connections facilitated stable gradient propagation, preventing degradation in deeper layers.

Compared to conventional CNN architectures, LSTM-based recurrent networks, and hybrid approaches reported in recent literature, the proposed method achieved superior predictive accuracy, with R^2 values reaching up to 0.9969 for motor speed prediction. These improvements highlight the efficiency of combining residual connections with dilated convolutions in capturing both fast-changing operational variables and slow thermal dynamics.

Such performance makes the framework particularly well-suited for real-time PMSM monitoring, predictive control, and condition-based maintenance applications, where early detection of operational anomalies is essential for ensuring safety, reliability, and efficiency.

To further evaluate the performance of the proposed Residual Dilated 1D-CNN framework, a comparative analysis with relevant studies in the literature was conducted (Table 5). The comparison covers both data-driven deep learning models and physics-based approaches, providing a broad perspective on predictive modeling strategies for PMSM operational parameters. Notably, the

proposed model outperforms previous works in terms of determination coefficient (R^2) and error metrics, achieving superior accuracy across all target variables.

Table 5 Comparison of the proposed model with related studies in the literature

| Study | Model / Method | Targets Predicted | Dataset | Best R^2 | Best RMSE | Key Findings |
|-------------------------------------------------------|--------------------------------|------------------------------------------|------------------------|------------|------------|---------------------------------------------------------------------------------------------|
| Kirchgässner et al. (2021) (Kirchgässner et al. 2021) | Deep Residual Neural Network | Motor temperature | Real PMSM dataset | 0.97 | 3.20°C | High accuracy for temperature prediction, but limited to thermal parameters |
| Vansompel et al. (2014) (Vansompel et al. 2014) | Lumped Parameter Thermal Model | Stator & rotor temperature | Experimental PMSM data | 0.94 | 4.10°C | Physics-based model; slower inference and limited adaptability |
| Nguyen et al. (2023) (Nguyen et al. 2023) | LSTM Network | Motor speed & torque | Industrial PMSM data | 0.95 | 125 rpm | Effective for dynamic speed prediction, but higher inference time |
| Zhang et al. (2022) (Zhang et al. 2022) | 1D-CNN | Motor speed | Simulated PMSM data | 0.96 | 110 rpm | Good for speed prediction; no multi-target capability |
| Proposed Model (This Study) | Residual Dilated 1D-CNN | Motor speed, stator yoke & winding temp. | Real PMSM dataset | 0.9969 | 101.89 rpm | Best accuracy across all targets; captures both short- & long-term dependencies efficiently |

As shown in Table 5, prior studies such as Kirchgässner et al. (2021) (Kirchgässner et al. 2021) and Vansompel et al. (2014) (Vansompel et al. 2014) demonstrated strong performance in thermal prediction tasks, while Nguyen et al. (2023) (Nguyen et al. 2023) and Zhang et al. (2022) (Zhang et al. 2022) achieved competitive results in speed forecasting. However, these methods are either limited to a single target or require higher computational resources. In contrast, the proposed approach delivers high-accuracy multi-target predictions while maintaining computational efficiency, making it particularly suitable for real-time

PMSM monitoring, predictive control, and condition-based maintenance applications.

CONCLUSION

This study proposed a Residual Dilated One-Dimensional Convolutional Neural Network (1D-CNN) framework for short-horizon multi-target prediction of key Permanent Magnet Synchronous Motor (PMSM) operational parameters, namely motor speed, stator yoke temperature, and stator winding temperature. By combining dilated convolutions and residual connections, the model effectively captured both short- and long-term temporal dependencies while maintaining computational efficiency.

Experimental results demonstrated that the proposed model achieved exceptional predictive performance, with determination coefficients (R^2) exceeding 0.96 for all targets and an average R^2 of 0.9829. Low error values in Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) metrics further validated the robustness of the approach.

Compared to conventional machine learning methods such as Gradient Boosted Regression Trees (GBRT) and Random Forests, as well as deep learning architectures like standard 1D-CNNs and LSTM-based models reported in the literature, the proposed framework consistently achieved higher accuracy while requiring less computational time for inference. The integration of dilated convolutions allowed for the efficient modeling of extended temporal dependencies without increasing parameter complexity, and residual connections ensured stable gradient flow, mitigating performance degradation in deeper architectures.

These advantages position the proposed framework as a strong candidate for real-time PMSM monitoring, predictive control, and condition-based maintenance applications, where early anomaly detection is crucial for safety, reliability, and operational efficiency. Future research will focus on expanding the dataset with additional operational parameters, validating the approach on various motor types, and exploring transfer learning and domain adaptation techniques to enhance generalization under diverse operating conditions.

Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

Availability of data and material

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Declaration of generative AI and AI-assisted technologies in the writing process

The authors declare that generative artificial intelligence (AI) tools were used during the preparation of this manuscript. Specifically, AI assistance was utilized for language editing, text refinement, and formatting purposes. The authors take full responsibility for the content and have carefully reviewed and verified all AI-assisted outputs.

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