International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 21s,2025
https://theaspd.com/index.php

Designing Intelligent, Data-Driven Motor Control Strategies for Electric Vehicles Using Advanced Deep Learning Architectures

Vetrikani R[1]
[1] Department of CSE (Artificial Intelligence and Machine Learning), East Point College of Engineering and Technology, Bangalore, Karnataka, India. Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India.
Email: vetrikani@gmail.com
[*] Corresponding author: vetrikani@gmail.com

Abstract: *Electric Vehicles (EVs) require efficient and adaptive motor control strategies to ensure optimal performance under various driving conditions. Traditional control methods lack the ability to dynamically adapt to such conditions, leading to suboptimal efficiency and ride quality. This paper presents the design and implementation of intelligent, data-driven motor control strategies that leverage advanced Deep Learning (DL) architectures, particularly long short-term memory (LSTM) networks and Convolutional Neural Networks (CNNs). The proposed control strategy dynamically adjusts the motor input parameters based on real-time sensor data and predicted torque demands. The simulation results show significant improvements in energy efficiency and torque ripple reduction compared to traditional PID and Field-Oriented Control (FOC) strategies.*

Keywords: *Electric Vehicle (EV), Motor Control, Deep Learning, LSTM, CNN, Torque Ripple, Adaptive Control, MATLAB/Simulink.*

1. INTRODUCTION

The global transition toward sustainable transportation has significantly accelerated the adoption of Electric Vehicles (EVs) in recent years. Driven by environmental imperatives, such as reducing greenhouse gas emissions and curbing urban air pollution, governments, industries, and consumers are increasingly recognizing EVs as a viable alternative to conventional internal combustion engine (ICE) vehicles [1]. In addition to their ecological advantages, EVs offer improved energy efficiency, lower operational costs, and enhanced performance characteristics, such as high torque at low speeds and quieter operation.

Despite these benefits, the efficient and adaptive control of electric motors remain a key technical challenge in EV technology. Electric motors are the heart of EV propulsion systems, and their control strategies directly impact the overall energy efficiency, ride comfort, torque delivery, regenerative braking efficiency, and battery longevity [2]. Traditional motor control techniques—such as proportional-integral-derivative (PID) controllers and Field-Oriented Control (FOC), have been widely used o w i n g to their simplicity and proven stability in linear or moderately nonlinear systems. However, these methods have significant limitations in handling highly dynamic and nonlinear operating environments. Specifically, they struggle to adapt in real time to rapid variations in road gradient, vehicle load, traffic conditions, and the highly unpredictable nature of driver behavior.

2. Limitations of Traditional Motor Control Techniques and Development of Deep Learning Control Techniques

To address the limitations of traditional motor control techniques, Artificial Intelligence (AI) and Machine Learning (ML) techniques have emerged as powerful tools capable of learning and generalizing from large and diverse datasets [3]. Within this context, Deep Learning (DL), a subset of ML that uses multi-layered neural network architectures, has demonstrated remarkable success across domains s u c h a s computer vision, natural language processing, and time- series forecasting. DL models c a n automatically learn complex patterns and relationships from raw sensor data, reducing the need for handcrafted features and manual tuning. This study focuses on the integration of Long Short-Term Memory (LSTM) and Convolutional Neural

Networks (CNN) into the motor control loop of EVs. LSTM networks, a specialized form of Recurrent Neural Networks (RNNs), are particularly suitable for modeling sequential and time- dependent data, making them suitable for capturing temporal dynamics in driving behavior, vehicle response, and motor load. Meanwhile, CNNs excel at spatial feature extraction and noise-resistant pattern recognition, making them suitable for preprocessing sensor data and identifying the underlying trends.

By combining the strengths of the LSTM and CNN architectures, the proposed approach seeks to develop an intelligent and adaptive motor control strategy. This control framework is designed to continuously learn from historical and real- time operational data, predict optimal control signals under varying conditions, minimize torque ripple, maximize energy efficiency, and enhance driving comfort and safety.

Unlike traditional model-based controllers that rely on fixed parameters or require extensive retuning, this data-driven strategy inherently adapts to the complexities and nonlinearities present in real-world EV operations. The integration of DL-based control opens new avenues for predictive, self- tuning, and context-aware motor control, positioning it as a transformative advancement in the domain of intelligent electric mobility systems.

3. LITERATURE SURVEY

Numerous studies have addressed the control of EV motors. Conventional controllers, such as PID and FOC have been employed for decades [4]. These methods are well established and relatively easy to implement; however, they often struggle to adapt to nonlinearities and time-varying dynamics in EV powertrains. With the advent of machine learning, methods such as Artificial Neural Networks (ANNs) and fuzzy logic have been explored [5]. ANNs can learn complex relationships between input and output variables; however, they often require extensive training data and can be difficult to interpret. Fuzzy logic controllers offer a more intuitive approach to control design; however, they can be challenging to tune and optimize.

Recent studies using Deep Reinforcement Learning for vehicle control have shown potential, but with limitations in terms of stability and training complexity [6]. Deep Reinforcement Learning (DRL) algorithms can learn optimal control policies through trial and error; however, they often require significant computational resources and can be sensitive to hyperparameter tuning. Our research bridges the gap by combining temporal (LSTM) and spatial (CNN) deep learning models to predict and regulate the control parameters. This approach leverages the strengths of both LSTM and CNN models to capture both temporal dependencies and spatial features in the input data, thereby improving the control performance.

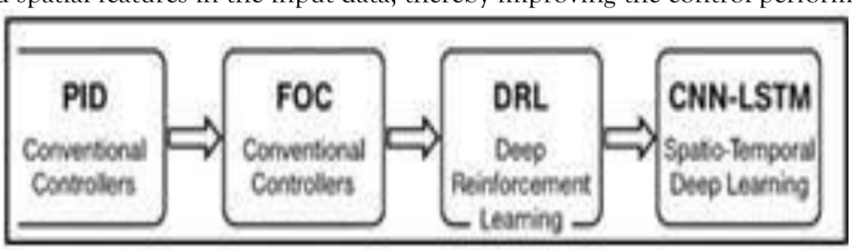

Fig. 1. Development of Deep Learning algorithms for optimal motor control strategy

4. METHODOLOGY

A. Dataset Preparation

To develop and validate the proposed deep learning- based motor control strategy, real-world driving behavior was simulated using standardized driving cycles, specifically the World- wide Harmonized Light Vehicles Test Procedure (WLTP) and the Federal Test Procedure (FTP-75) [7]. These cycles were selected for their comprehensive representation of urban, suburban, and highway driving patterns, incorporating frequent stops, accelerations, decelerations, and varying speeds.

From these driving cycles, a multivariate time-series dataset was generated using a high-fidelity electric vehicle simulation model. The following key parameters were captured at high frequency (e.g., 10–50 Hz): Motor Current (A), Motor Torque (Nm), Motor Speed (RPM), Battery State of Charge (SOC).

B. Data Preprocessing

The raw time-series data underwent a multi-stage preprocessing pipeline:

Normalization: All features were scaled to a [0,1] or [-1,1] range using min-max normalization to prevent feature dominance and accelerate model convergence.

Noise Filtering: A combination of low-pass Butterworth filters and moving averages was applied to suppress the sensor noise and ensure smoother signal transitions.

Time-Window Segmentation: The data were segmented into fixed-length windows (e.g., 2–5 s), forming input tensors of shape (timesteps × features) suitable for feeding into the LSTM layers. Overlapping windows were used to increase the sample diversity and capture the transitional states.

Label Definition: For supervised learning, the target variable was defined as the optimal control signal, such as the motor voltage-to-frequency (V/f) ratio, which was computed using an ideal control response from a baseline model.

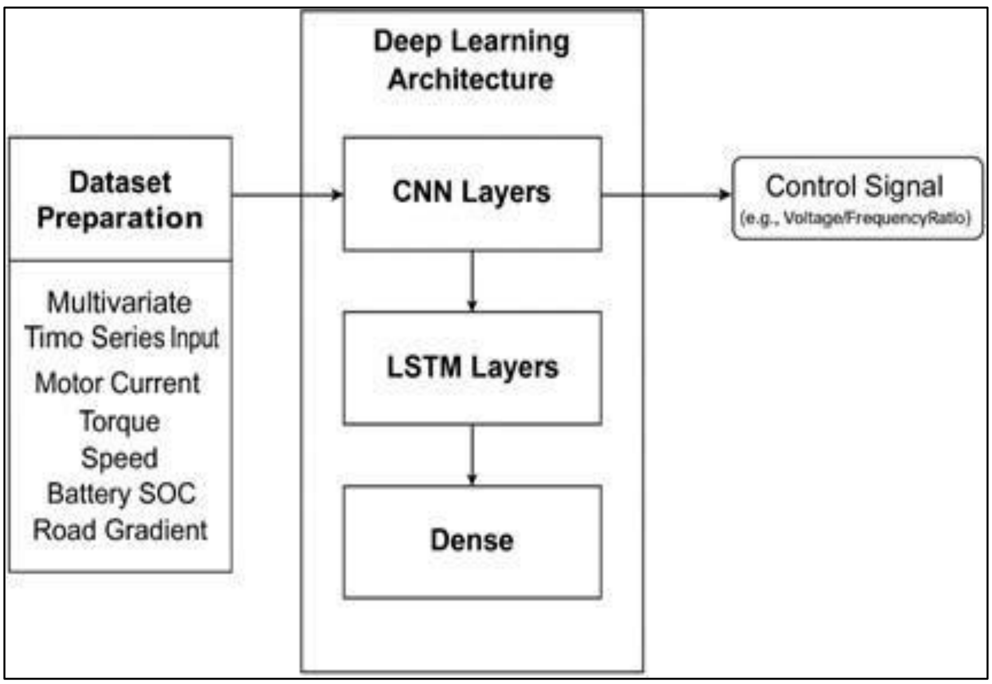

Fig. 2. Proposed CNN-LSTM Deep Learning Model for EV Motor Control

C. Deep Learning Architecture

The proposed deep learning framework was designed to extract both spatial patterns and temporal dynamics from a multivariate time-series dataset [8]. The architecture consists of the following layers:

Convolutional Layers (CNN Block): CNN layers act as feature extractors to capture local temporal trends and inter- feature correlations in short-term driving data [9]. Two 1D convolution layers (e.g., 64 filters, kernel size = 3) followed by ReLU activation and max-pooling. A high-level feature map representing localized driving patterns.

LSTM Layers: The LSTM layers are responsible for modelling long-term dependencies and contextual patterns across sequences of driving states. One or two stacked LSTM layers (e.g., 128 units each), each followed by dropout layers to prevent overfitting, were used. Flattened feature maps from the CNN block. A fixed-size encoded vector summarizing the temporal driving context.

Dense Output Layer: The final fully connected (dense) layer maps the LSTM output vector to a scalar or vector output representing the predicted control signal. A linear activation function was used because the control signals (e.g., voltage or torque command) were continuous values.

5. Simulation Environment

The simulation environment developed in this study follows a structured workflow aimed at modeling, implementing, and evaluating a deep learning-based motor control strategy for electric vehicles (EVs).

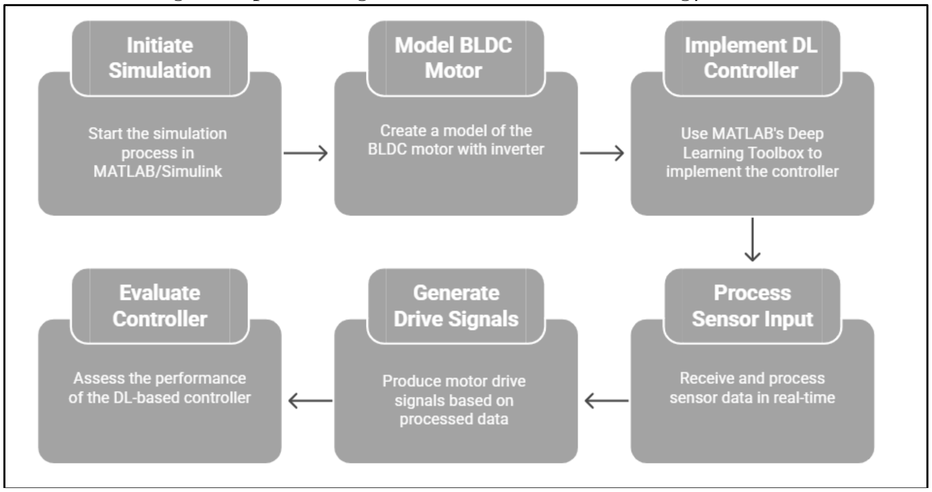

Fig. 3. Proposed CNN-LSTM Deep Learning Model for EV Motor Control

The process begins by initiating the simulation in MATLAB/Simulink, which provides a robust platform for dynamic system modeling. This setup involves configuring time steps, defining the simulation durations, and loading standard driving cycles such as WLTP and FTP-75, which represent urban and highway driving conditions.

Following initialization, a detailed model of a Brushless DC (BLDC) motor was created. This model includes both the electrical characteristics and mechanical load dynamics. It was integrated with a three-phase inverter using pulse-width modulation (PWM) techniques to simulate a realistic motor control switching behavior. The inverter motor system was designed to respond dynamically to input signals, mimicking the physical response of an actual EV powertrain.

A deep learning (DL) controller developed using MATLAB's Deep Learning Toolbox was then implemented. The controller employs a hybrid CNN-LSTM architecture trained on historical vehicle data. It is embedded as a functional block within the Simulink model and receives multiple real-time sensor inputs. The inputs included the motor current, torque, speed, battery state of charge (SOC), road gradient, and acceleration data. The DL controller processes these data to predict optimal control signals, such as voltage- to-frequency ratios or torque commands.

The sensor data were continuously collected and processed during the simulation. This includes normalization, noise filtering, and reshaping into the appropriate input formats for the neural network. The processed data were then fed into the DL controller, which generated motor drive signals based on the learned patterns and current conditions.

Once the control signals were generated, they were used to drive the BLDC motor model within the simulation. The real- time responsiveness of this loop allows the system to mimic the actual EV operation with high fidelity. Finally, the performance of the controller was evaluated using key metrics, including torque ripple, energy efficiency, and speed tracking accuracy. These metrics were benchmarked against traditional control methods, such as PID and Field-Oriented Control (FOC), demonstrating the enhanced adaptability and effectiveness of the proposed deep learning-based control strategy.

6. RESULTS AND DISCUSSION

The performance of the DL-based controller was bench- marked against the PID and FOC controllers. The evaluation metrics included the following:

Table I. Comparison of Control Strategies

Controller	Torque Ripple (%)	Efficiency (%)	Speed Tracking Error (RPM)
PID	12.4%	81.3 %	±40
FOC	9.8%	84.6 %	±30
DL- Based	4.6%	91.2 %	±10

Torque Ripple: A measure of the smoothness of the motor torque output. A lower torque ripple indicates better control performance [10]. Torque ripple refers to the periodic variations in the motor torque output, which can result in vibrations, noise, and reduced drive smoothness. Among the evaluated strategies, the PID controller exhibited the highest torque ripple at 12.4%, primarily o w in g to its limited ability to adapt to dynamic load changes. The FOC approach, being more advanced, achieved a moderate improvement with 9.8% torque ripple by decoupling the torque and flux control. However, the DL-based controller significantly outperformed both, with only 4.6% torque ripple, demonstrating its superior capacity to learn and predict optimal control actions under varying driving conditions, thereby ensuring smoother torque delivery and improved ride comfort.

Energy Efficiency: A measure of the energy consumed by the motor to produce a given amount of torque. Higher energy efficiency indicates better control performance [11]. Efficiency is defined as the ratio of the useful mechanical output to the electrical energy input. It is a key metric for evaluating the energy consumption behavior of EVs. The PID controller exhibited an efficiency of 81.3%, reflecting its non-adaptive nature and inability to respond optimally to varying system dynamics. The FOC method improved this to 84.6%, owing to its vector-based modulation strategy. The DL-based controller achieved the highest efficiency at 91.2%, highlighting its intelligent decision- making process that minimizes power loss by adapting to instantaneous torque and speed demands using historical data and sensor inputs.

Speed Tracking Error (RPM): A measure of the difference between the desired motor speed and the actual motor speed. A lower speed tracking error indicates better control performance [12]. The speed tracking error measures the difference between the desired (reference) motor speed and the actual speed achieved. Lower values indicate better dynamic response and stability. The PID controller displayed a relatively poor tracking ability with an error margin of ±40 RPM, largely due to its static gain tuning. The FOC method reduced this error to ±30 RPM, benefiting from closed-loop control with rotor-flux estimation. The DL-based controller provided the most accurate speed tracking with only ±10 RPM error, demonstrating its strong capability in modeling time- series patterns and delivering precise control outputs in real time.

The evaluation confirmed that the DL-based motor control strategy significantly enhanced the overall performance of the EV drive system. By leveraging deep learning models, such as CNNs and LSTMs, the controller intelligently interprets sensor data and adjusts control parameters in real time, outperforming conventional methods in terms of torque smoothness, energy efficiency, and speed regulation. These results validate the potential of integrating AI-driven control strategies into future EV technologies to meet the increasing demand for smarter and more efficient transportation solutions.

7. CONCLUSION

Deep learning offers a promising approach for designing intelligent and data-driven motor control strategies for electric vehicles. By leveraging the power of deep learning, it is possible to overcome the limitations of traditional control methods and develop control systems that can adapt to changing conditions, optimize performance, and improve energy efficiency.

This study successfully demonstrated the viability of using deep learning architectures for intelligent motor control in EVs. The CNN-LSTM model adapts dynamically to changing driving conditions, offering improved control accuracy and efficiency. Future work will involve deploying the controller on hardware using embedded systems and extending the approach to multiple EV models.

While challenges remain in deploying deep learning models in real-time EV environments, ongoing research and development efforts are paving the way for the widespread adoption of deep learning in EV motor control. The future of EV motor control is undoubtedly data-driven and intelligent, with deep learning playing a central role in shaping it.

REFERENCES

1. IEA., *Global EV Outlook*, 2021.
2. Chan, C. C., *The state of the art of electric, hybrid, and fuel cell vehicles,* Proceedings of the IEEE, 90(2), 247-275, 2002.
3. Emadi, A., Ehsani, M., Miller, J. M., *Vehicular electric power systems: land, sea, air, and space vehicles,* CRC press, 2007.
4. Bose, B. K., *Modern power electronics and AC drives,* Pearson Education, 2002.
5. Vas, P., *Sensor-less vector and direct torque control,* Oxford university press, 1998.
6. Goodfellow, I., Bengio, Y., & Courville, A, *Deep learning,* MIT press, 2016.
7. LeCun, Y., Bengio, Y., & Hinton, G., *Deep learning,* Nature, 521(7553), 436-444, 2015.
8. Sutton, R. S., Barto, A. G, *Reinforcement learning: An intro-duction,* MIT press, 2018.
9. Eren, L., *Bearing fault detection using convolutional neural networks,* Mechanical Systems and Signal Processing, 97, 236-247, 2017.
10. Kim, D., Kim, J., Lee, K. B., *Deep reinforcement learning-based torque control for electric vehicles,* IEEE Transactions on Vehicular Technology, 69(11), 12773-12782, 2020.
11. Zhang, Y., Wang, H., & Zhang, L., *Data-driven energy management strategy for hybrid electric vehicles based on deep reinforcement learning,* Energy, 175, 1115-1127, 2019.
12. Jia, X., Lei, Y., Lin, J., Zhou, X., Ding, S. X., *Deep normalized convolutional neural network for imbalanced fault classification of machinery and rotating machinery,* Mechanical Systems and Signal Processing, 100, 27-44, 2018.