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A Hybrid DNN–PSO Control Framework for Electric Vehicle Motor Drives with Optimized Power Modulator Design

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Abstract

Control algorithms that can consistently handle nonlinear motor behavior and constantly shifting operating conditions are necessary to achieve excellent performance and energy economy in electric vehicle propulsion systems. To improve the performance of traditional PID-based motor control systems, this study presents a hybrid intelligent control approach that combines a deep neural network with particle swarm optimization. To improve transient responsiveness, robustness, and energy efficiency, PSO is used to optimize the controller parameters, while a DNN is used to capture the nonlinear dynamic features of EV traction motors. Through extensive MATLAB/Simulink simulations of brushless DC, switching reluctance, and AC series motors under various speed commands and load disturbances, the efficacy of the proposed DNN–PSO controller is evaluated. Performance comparisons with classical PID and ANN-based controllers indicate a noticeable reduction in torque ripple, reaching up to 1.8%, along with a faster speed response, with a rise time of approximately 0.6 s, and an overall efficiency improvement of up to 92.6%. In addition, the suggested control technique exhibits better disturbance rejection and superior transient performance, notably in reluctance and AC series motor drives. The outcomes verify that the suggested hybrid control framework is appropriate for high-performance and energy-efficient EV propulsion applications

Keyword: Electric Vehicle, Motor Control, Power Modulator Design, Deep Neural Network, Particle Swarm Optimization, Energy Efficiency

1. Introduction

This section gives an overview of electric vehicle motor drives, their control requirements, and the major issues associated with power modulation. It also discusses conventional and emerging control methods, including AI-based approaches, to provide a background for understanding the development of the proposed DNN–PSO control framework.

1.1 Background and Motivation

People are worried about climate change, running out of fossil fuels, and tough pollution restrictions, electric cars (EVs) are becoming very popular very quickly. Because they don't pollute the air and use renewable energy sources, EVs are considered a sustainable alternative [1]. The electric motor, power modulator, and control unit work together to improve the performance and efficiency of EV propulsion systems [2–3]. Power electronic converters operate EV motors by varying the voltage and current according to the car's driving conditions [4]. The PID, Field-Oriented Control (FOC), and Direct Torque Control (DTC) methods are commonly used to monitor EV performance and efficiency [5]. But with EV propulsion systems, temperature fluctuations, parameter aging, load disturbances, and battery voltage changes can all happen. Among them, PID, Field-Oriented Control (FOC), and Direct Torque Control (DTC) are widely used control approaches, as they are simple and easy to understand [5]. However, since EV propulsion systems are nonlinear and affected by temperature changes, parameter aging, load disturbances, and battery voltage fluctuations, classical controllers perform very poorly [6, 7]. Recent advances in AI and machine learning have made it possible to use adaptive, data-driven control methods. The formation of hybrid control systems involves the following optimization techniques: neural networks, fuzzy logic, and evolutionary optimization, which make systems more durable and efficient, enabling electric vehicles to run better and use less energy [8]. Figure 1 shows a schematic diagram of the EV propulsion and control system.

1.2 Challenges in EV Motor Control and Power Modulation

Despite such enormous advancements, EV motor control and power modulation still suffer from significant inconsistencies in nonlinearity, parameter uncertainty, and real-time operation. Electric vehicle (EV) traction motors operate under extreme conditions across a broad range of RPMs and torques and typically switch between motoring and regenerative braking. This results in very strong nonlinearities, which make those fixed-gain controllers less applicable [9]. As the motor ages and gets warmer, its stator resistance, inductance, and permanent magnet flux change. This causes torque ripple and reduces performance [10]. Adding switching losses, dead-time effects, harmonic distortion, and thermal stresses to the power modulator makes everything even more complex. EV-based control systems also have to satisfy stringent real-time conditions. Complex algorithms such as MPC and deep learning-based approaches require substantial computational resources, making them difficult to deploy in practice [11]. The second problem is to produce good performance in driving conditions. Road slope, vehicle weight, aerodynamic drag, and the driver's behavior may make it more challenging to control an automobile's performance [12]. And to improve the design's sophistication, motor drive and battery management must work hand in hand to enhance system energy efficiency and prolong battery life [13]. These issues demonstrate the need for smart, flexible controls to ensure EVs operate well and safely.

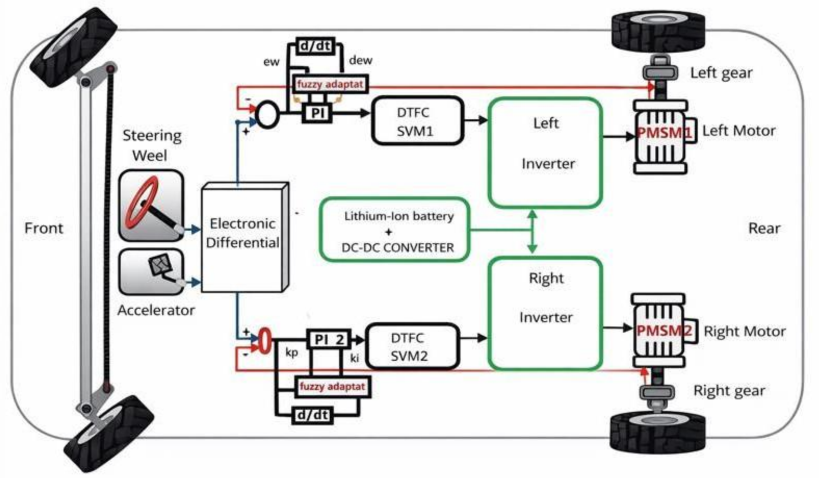


Figure 1: EV propulsion and control systems schematic diagram [8]

1.3 Limitations of Conventional Control Techniques

These types of traditional control methods (such as PID, FOC, or DTC) remain the most popular in electric vehicle motor drives, owing to their simplicity and rigorous theoretical basis, and continue to dominate them. However, their effectiveness depends on precise motor models and static controller parameters and thus limit their operation in real-life driving tests. PID controllers are sensitive to dynamic fluctuations in the parameter and the load, resulting in greater steady-state error, overshoot, and torque ripple as motor properties change due to temperature elevation or aging. Field-Oriented Control (FOC) enables relatively independent torque and flux regulation, provided accurate rotor position and parameter estimates are available. Parameter mischaracterization and sensor measurement biases degrade efficiency and dynamic performance, and inverter non-ideal ties, such as dead time and voltage drops, aggravate control accuracy. These considerations are critical in electric vehicles, as seamless torque and optimized efficiency are essential for driving comfort and battery life. Model Predictive Control (MPC) offers performance improvements while requiring high-quality system models and substantial computational power to be practical for embedded electric vehicle controllers and to be open to model uncertainties [12, 14].

1.4 Powertrain for Electric Vehicles

The electric vehicle (EV)'s primary component for converting stored electrical energy into mechanical motion is called a powertrain. It performs extremely well and reliably. In contrast to conventional powertrains that rely on internal combustion engines, EV powertrains primarily use batteries or hybrid energy storage systems as the power source; the battery is complemented by power electronic converters and an electric traction motor, along with a control unit that orchestrates power flow and torque generation [15]. A battery pack supplies direct current (DC) to a voltage source inverter (VSI), which converts it into controlled alternating current (AC) that drives the drive motor. EVs employ various types of electric motors, including Induction Motors (IMs), Brushless DC Motors (BLDCs), and Permanent Magnet Synchronous Motors (PMSMs). As they are small, efficient, and have high power density, PMSM and BLDC motors are used in many cars [16]. And this makes them a great choice for high-performance passenger vehicles as well. Induction motors remain a suitable choice for cost-effective designs that do not require magnets, as they are strong and require less rare-earth material [2]. Power electronic converters are extremely useful in electric vehicles, as they provide precise control over motor speed and torque while harnessing the stored energy for conversion. Since all the advancements in wide-band gap semiconductors have been made converter switching frequency, power density, and heat performance have been significantly improved over those achieved with traditional silicon-based devices. The EV powertrain has to perform well for so many different driving situations - speed up, cruise, go up hills, regenerative stopping. Additionally, integrating energy management strategies and car dynamics control is essential to improve system performance and increase driving range. Figure 2 presents the schematic model of the EV powertrain.

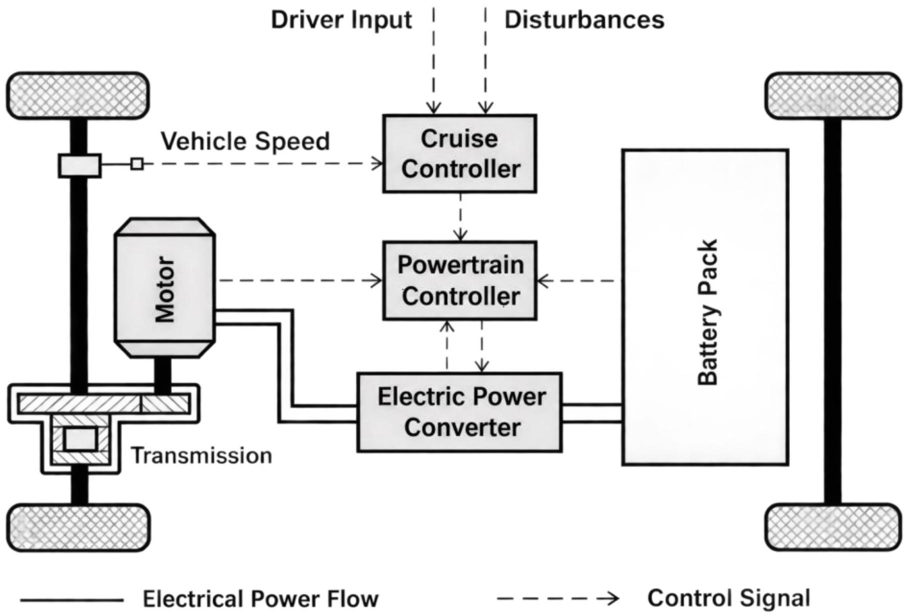
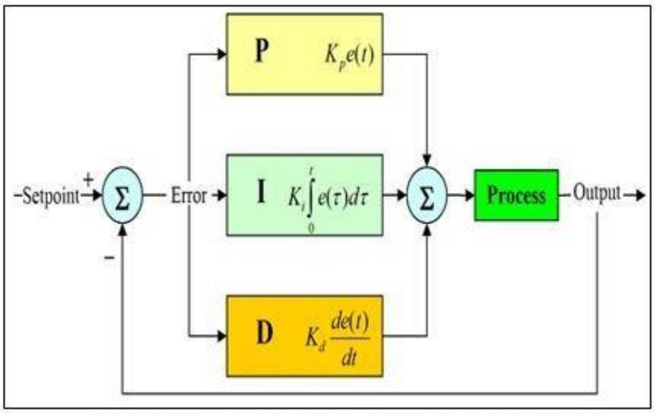


Figure 2: Schematic diagram of the EV powertrain including cruise control system [17]

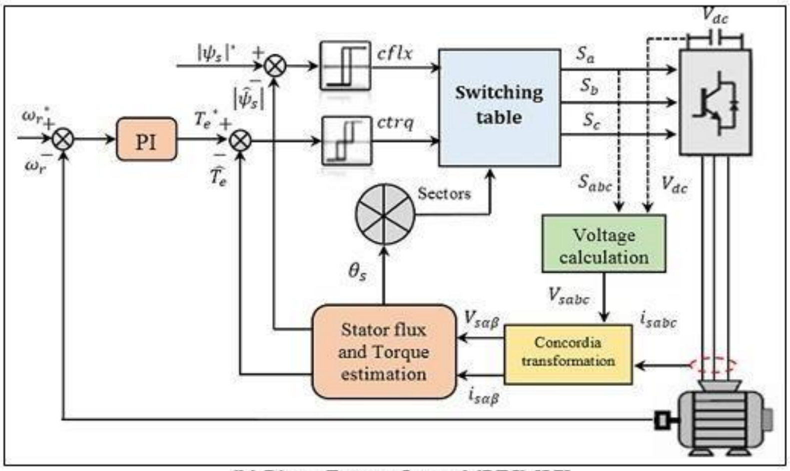
1.5 Traditional and New Approaches to the Control of Motion

Traditional motor control schemes such as Proportional–Integral–Derivative (PID) control, Field-Oriented Control (FOC), and Direct Torque Control (DTC) are widely used in electric vehicle (EV) traction systems due to their convenience, solid theoretical foundation, and ease of real-time implementation. Under standard loading conditions such controllers achieve acceptable performance and are computationally efficient for embedded drive applications. Existing controllers rely heavily on exact mathematical models and model-based parameters. In the real world of electric vehicle operation, temperature variation, magnetic saturation, inverter nonlinearity, and aging behavior cause parameter drift, leading to decreased speed-tracking precision, a surge in torque ripple, and increased energy loss [18, 19]. Thus, standard control mechanisms often fail to maintain optimal behavior in very dynamic driving conditions, such as stop-and-go traffic, regenerative braking, and load disturbances. Model Predictive Control (MPC) has been developed as an advanced control approach for electric vehicle motor drives, where the system limitations are taken into consideration and predicted actions have a finite time-horizon with respect to the control options [20]. In recent literature, we have found that Model Predictive Control (MPC) can show a significantly superior transient response, diminish torque ripple, and improve disturbance resilience compared with Proportional-Integral Field-Oriented Control (PI-FOC) methods [21]. However, Model Predictive Control (MPC) suffers from high computing complexity and model discrepancies, thus limiting its immediate deploy ability in inexpensive real-time embedded controllers for high-speed traction drives [22]. Data-driven and learning-based control methods have gradually been leveraged to overcome such limitations. The advanced machine learning techniques demonstrate strong performance in addressing nonlinearities and uncertainties in electric vehicle (EV) propulsion systems [23–24]. They can also directly learn the intricacies of motor–inverter dynamics from operational data, enabling adaptive control without requiring specific physical models. Neural network-assisted FOC and PSO-tuned PI controllers have been reported to achieve a 30% reduction in torque ripple and improved efficiency across fvaried load configurations [25]. Traditional motor control operations are shown in Figure 3 (a) Proportional–Integral–Derivative (PID) control and Figure 3 (b) Direct Torque Control (DTC).

Furthermore, deep reinforcement learning-based systems for speed and torque control have demonstrated strong performance even under unknown driving cycles, such as WLTP and NEDC [28]. Nevertheless, most AI controllers are offline-trained and heavily depend on diverse, high-quality datasets. Yet, even with the existing advances, generalization towards peculiar and extreme operational conditions still presents challenges [29]. Just as critical for safety-oriented EV solutions are stability guarantees and transparency, neither of which is always present in purely data-driven controllers. Therefore, hybrid intelligent control methods that integrate model-based control and data-driven optimization have recently been a focus of research. Such techniques make capitalizing on the stability and fast response time of traditional controllers, while making optimizations and adaptive methods available to manipulate parameters and reject anomalies. Hybrid designs such as these will serve future electric vehicle motor control systems well, not least because they offer an agreeable compromise among speed, reliability, and real-time operation.



(a) Proportional–Integral–Derivative (PID) control [26]



(b) Direct Torque Control (DTC) [27]

Figure 3: Traditional motor control strategies

1.6 Hybrid AI-Inspired Motor Control Schemes

Classical model-based controllers integrate artificial intelligence and optimization to leverage both methods in hybrid AI-inspired motor control schemes. Traditional control algorithms (PI/FOC and MPC) provide stability and quick response, whilst artificial intelligence algorithms (such as Deep Neural Networks (DNNs), fuzzy logic, and evolutionary optimization algorithms) make them more adaptable and robust in dynamic scenarios that include nonlinearities and uncertainty [27]. The hybrid controller outperforms both the pure classical and the all data-driven controllers in EVs. It has been shown that neural-network-assisted FOC schemes can overcome parameter variations induced by temperature rise, magnetic saturation, and load disturbances [24]. Accordingly, fuzzy logical adaptive controllers of the flexible motors controlled by PI, combined with control circuit integration into the PI system, will allow the precise speed management on highly dynamic driving scenarios. Well-optimized hybrid approaches have also been investigated. In real-time or semi-online applications, Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Differential Evolution (DE) are most often used to tune controller gain and weighting factors. Compared to fixed-gain controllers for PMSM and BLDC drives, PSO-tuned PI and MPC controllers have shown a significant reduction in torque ripple of 25–35% and improved transient response to the application speed. Hybrid DNN–MPC and DNN–FOC controllers that preserve the stability structure of model-based control systems rely on simulating the nonlinearities of motor–inverter dynamics using neural networks [29]. Hybrid schemes have also improved with the use of reinforcement learning (RL) to tailor torque and flux control policies during load and driving cycles, such as WLTP and NEDC. Compared with classical adaptive controllers, this approach has proven much more versatile. Although these hybrid AI controls yield promising results, most existing hybrid AI controller methods rely on offline training and relatively simple thermal constraints and assumptions about inverter dynamics. Their generalizability to extreme or previously unseen operational conditions remains limited. Moreover, many studies focus on optimizing only one control layer (eg, gain tuning or reference generation), but neglect to integrate inverter switching behavior, torque regulation, flux control, speed control, and regulation optimization. Consequently, current research trends focus on the construction of streamlined hybrid control architectures that are both real-time optimized and machine-learning integrated to control multiple objectives simultaneously. Such coordinated frameworks can handle the nonlinear behavior of motors, the non-ideality of power electronics, and the vagaries of operation within a single adaptive control loop in a single integrated system. These hybrid AI-inspired schemes offer a viable solution for developing advanced EV motor drive systems, as they strike a pragmatic balance among computational capability, higher efficiency, and reliability.

2. Methodology

This section introduces the suggested hybrid Deep Neural Network–Particle Swarm Optimization (DNN–PSO) control architecture for electric vehicle (EV) motor drives. The methodology encompasses system architecture, mathematical modelling, control design, intelligent optimization, coordinated motor-inverter control, and a validation framework.

2.1 System Modelling of the EV Motor

In the current study, we discuss an electric vehicle (EV) powertrain comprising a traction motor, a voltage source inverter (VSI), a DC battery supply, and a digital control unit. In the synchronous d–q reference frame, the motor is modelled to provide generality and an accurate description of dynamic behavior. Stator voltages, currents, resistances, and inductances describe the electrical dynamics. In contrast, the electromagnetic torque is described as a function of the q-axis current and permanent magnet flux linkage. The hybrid control approach of DNN–PSO integrates the synergistic benefits of deep neural networks and particle swarm optimization to address nonlinear motor control issues. Deep neural networks are robust for modelling the complex dynamics of permanent magnet synchronous motor-based electric drives and enabling high-speed, real-time inference post-training. Still, their performance becomes less efficient in the presence of parameter uncertainties, load disruptions, or out-of-network cases for several factors. To overcome these limitations, PSO is implemented as an adaptive optimization layer that dynamically modifies fundamental control features and selected network weights in a population-based, gradient-free search, which may be close to global optima for nonlinear and limited-control issues. With the combination of DNN modelling and PSO-based optimization, the controller can maintain a fast dynamic response and greater resilience to changing operating conditions. In contrast to PI, fuzzy logic and other smart control techniques introduced in literature, the proposed DNN–PSO method significantly attenuates torque ripple and improves transient performance but keeps operation constant in condition of parameter uncertainties and external disturbances, and finds a good balance between modelling accuracy, adaptability and computational efficiency in next-generation high-performance electric vehicle motor drive systems.

For generality, the motor dynamics are modelled in the synchronous d_q reference frame

$$\boldsymbol{V_d = R_s i_d + L_d \frac{d_{i_d}}{dt} - \omega_e l_q i_q} \quad (1)$$

$$\boldsymbol{V_q = R_s i_q + L_q \frac{d_{i_q}}{dt} - \omega_e (l_d i_d + \psi_f)} \quad (2)$$

Where V_d, V_q: are the stator voltages, i_d, i_q: are the stator currents, R_s, is stator resistance, $l_d i_q$ are inductances, ω_e is electrical angular speed, ψ_f is permanent magnet flux linkage.

- The electromagnetic torque is given by:

$$\boldsymbol{T_e = \frac{3}{2} p\, [\psi_f i_q + (L_d - L_q) i_d i_q} \quad (3)$$

Where p denotes the number of pole pairs.

- Mechanical Dynamics

The rotor dynamics follow:

$$\boldsymbol{j \frac{d\omega m}{dt} = T_e - T_L - B\omega_m} \quad (4)$$

Where: j is the moment of inertia, B is the viscous friction coefficient, T_L is the load torque.

2.2 Field-Oriented Control Structure

As a result, FOC (Field-Oriented Control) is the primary control method in electric vehicle (EV) motor drive systems, as it can independently control torque and flux, similar to a DC motor with separate excitation. In this method, Clarke and Park transformations transform the three-phase stator currents into a synchronous rotating d–q reference frame. The d-axis current component controls the magnetic flux, and the q-axis current component directly controls the electromagnetic torque. Based on the speed error between the reference and actual motor speed, the outer speed control loop generates the reference torque current iq∗. In contrast, the flux reference current id∗ is usually set in accordance with the Maximum Torque per Ampere (MTPA) criterion to ensure efficient operation. The d- and q-axis currents are controlled by inner current control loops using proportional–integral (PI) controllers, generating corresponding voltage references vd∗ and vq∗. The voltage references are converted into inverter switching signals via Space Vector Pulse Width Modulation (SVPWM), enabling efficient utilization of the DC-link voltage and reducing harmonic distortion. In the proposed control framework, the fixed-gain PI controllers of the FOC scheme are supplemented by a hybrid DNN–PSO optimization layer, improving the ability to adjust control parameters and fine-tune performance in the presence of load variations, parameter uncertainties, and nonlinear motor behavior. However, instead of fixed PI gains, adaptive gain and reference optimization is done with a hybrid DNN–PSO framework.

2.3 Deep Neural Network–Based System Representation

A deep neural network (DNN) is used to model the nonlinear dynamics of the electric vehicle (EV) motor drive system and to compensate for uncertainties and disturbances adaptively. The nonlinear coupling between the electrical and mechanical subsystems in traction motors is so strong that standard linear models cannot capture the system's behavior across wide operating ranges. It is a data-driven representation learning the motor drive's varied input–output behavior across speed, load, and voltage. The input vector to the DNN includes all key state parameters, such as motor speed, stator currents in the d–q reference frame, load torque, and DC-link voltage. The output vector consists of corrective control signals or revised controller parameters, such as torque compensation and gain adjustments for the inner current and outer speed control loops. Using simulation or experimental data, one can train the DNN offline to reduce tracking errors between the reference and actual motor responses. After training, the DNN operates online to quickly produce real-time predictions and adapt to changes with low computational cost. A Particle Swarm Optimization (PSO) layer is attached to the DNN to repeatedly optimize certain network weights and control parameters, as DNN performance can drop off when it exceeds the training data limit. Through this hybrid representation of DNN-PSO, the reliable operation of the electric vehicle motor drive system is ensured, including when parameters vary or external disturbances act as the cause, while also enhancing transient responsiveness.

- DNN Input–Output Mapping

  The DNN approximates the nonlinear function:

  $$\boldsymbol{y}\,(\boldsymbol{k}) = \boldsymbol{f_{NNN}}(\boldsymbol{X}\,(\boldsymbol{K})) \tag{5}$$

  Where the input vector is defined as:

  $$\boldsymbol{x}\,(\boldsymbol{k}) = [\boldsymbol{\omega_{m,}} \boldsymbol{i_{d,}} \boldsymbol{i_{q,}} \boldsymbol{v_{dc,}} \boldsymbol{T_{L,}} \boldsymbol{\theta}] \tag{6}$$

  And the output vector is:

  $$\boldsymbol{y}\,(\boldsymbol{k}) = [\boldsymbol{\Delta i^{*}_{q,}}\ \boldsymbol{\Delta K_{p,}} \boldsymbol{\Delta K_{i}}] \tag{7}$$

  Representing adaptive torque reference correction and controller gain updates.

- Training Objective

  The DNN is trained to minimize the loss function:

  $$\boldsymbol{L} = \sum_{k=1}^{N}(\boldsymbol{\omega^{*}_{m}} - \boldsymbol{\omega_{m}})^{2} + \boldsymbol{\lambda}(\boldsymbol{Tr^{2}}) \tag{8}$$

  Where: ω^{*}_{m} is reference speed, T_r is torque ripple, λ is a weighting factor.

2.4 Particle Swarm Optimization for Multi-Objective Control

The use of Particle Swarm Optimization (PSO) as a multi-objective adaptive optimization mechanism to improve the performance of EV motor drive control systems under nonlinear and time-varying operating conditions. The main objectives of PSO process optimization are to minimize speed-tracking error, reduce torque ripple, and enhance transient response, while retaining energy efficiency and system stability. Each particle in the PSO framework represents a proposed set of controller parameters and DNN weights, which are iteratively updated based on the best individual and global solutions to the optimization problem. The optimization procedure is guided by a composite fitness function, which combines speed error, torque ripple, and power loss indices. By nature, the population-based, gradient-free search capabilities of PSO enable effective solutions to nonlinear and multimodal control problems without requiring an exact system model. PSO significantly enhances the robustness and dynamic performance of the proposed hybrid control system for EV propulsion by adjusting control parameters in response to load disturbances and parameter uncertainties.

- Optimization Variables:

  $$\boldsymbol{p} = [\boldsymbol{K_{p}},\ \boldsymbol{K_{i,}}\ \boldsymbol{\omega_{1}},\ \boldsymbol{\omega_{2,}}] \tag{9}$$

  Where: K_p, $K_{i,}$ are control gains and ω_{1}, $\omega_{2,}$ are weighting coefficients.

- Fitness Function: The PSO minimizes a multi-objective cost function:
$$j = \alpha_1 e_\omega^2 + \alpha_2 T_r^2 + \alpha_3 P_{loss} + \alpha_4 \Delta V_{dc} \quad (10)$$
Where: e_ω is speed error, P_{loss} represents inverter and copper losses, ΔV_{dc} is the DC-link voltage fluctuation.

- PSO Update Equations
$$v_i^{k+1} = \omega v_1^k + c_1 r_1 (p_i^{best} - X_i^k) + c_2 r_2 (g^{best} - X_i^k) \quad (11)$$
Where: c_1, c_2 are acceleration constants and $r_1, r_2 \in [0,1]$

2.5 Coordinated Motor–Inverter Control

A coordinated mode of motor-inverter control means that the motor and the power electronic inverter operate in concert rather than as separate entities. The motor controller first calculates the required voltage and current directives for the given speed and torque. These orders are generated by a field-oriented control (FOC) method; an FOC maintains the d and q-axis currents independently to control the flux and torque. The voltage source inverter (VSI) then converts the DC power from the battery into three-phase AC voltages, as specified in the reference directives. Space Vector Pulse Width Modulation (SVPWM) provides precise switching signals for inverter switches, enabling them to utilize the DC-link voltage with minimal harmonic distortion optimally. In the system presented here a DNN–PSO-based controller is employed that continuously modifies the control parameters to accommodate nonlinear motor dynamics, load fluctuations, and parameter uncertainties. Integration of the intelligent controller and inverter allows motor currents to be properly harmonized with reference values, resulting in smooth torque generation, reduced torque ripple, fast dynamic response, and energy savings. In general, the coordination of the motor–inverter control ensures stable, efficient, and high-performance operation of the EV propulsion system over a broad range of operating conditions. The optimized control signals are translated into inverter switching commands using space vector pulse width modulation (SVPWM):

$$V_{ref} = f(i^*d, i^*d, \theta) \quad (12)$$

Non-ideal inverter effects, such as switching losses and dead time, are incorporated into the control loop to improve robustness.

2.6 Algorithmic Flow of the Proposed DNN–PSO Control Scheme

The proposed DNN–PSO control scheme starts by comparing the reference speed with the actual motor speed to produce error signals, which are mixed with motor state variables (e.g., d–q-axis currents and DC-link voltage) and fed into the Deep Neural Network (DNN) as inputs. The DNN gives an initial estimate of control adjustments based on the learned nonlinear behavior of the system. Particle Swarm Optimization (PSO) then optimizes the controller parameters and selected DNN weights by minimizing a multi-objective fitness function that represents speed-tracking error, torque ripple, and power loss. These optimized parameters are used in the Field-Oriented Control (FOC) framework to generate reference voltages, which are converted to inverter switching signals using Space Vector Pulse Width Modulation (SVPWM). Figure 4 describes the Proposed Hybrid DNN–PSO Motor Control.

2.7 Simulation and Experimental Validation

This implementation is validated based on a three-stage verification framework using a combination of MIL, SIL, and HIL tests (MIL/SIL, HIL-hardware-in-the-loop implementation, MATLAB/Simulink real-time embedded control platform) for the proposed control method. It then combines the motor drive system, including the inverter, and vehicle dynamics with the given controller in MIL phase to test theoretical and real system performance under both good and bad conditions. The SIL phase allows testing and verification of validated control algorithms in real time and evaluation of numerical stability, computational performance, and controller reliability. In the HIL stage, the control algorithm is verified experimentally using actual hardware components, such as digital signal processors (DSPs) or microcontrollers, to interface with the control algorithm and to replicate the plant process in real time, simulating realistic operational conditions. Validation scenarios are set up, with reference speed tracking for transient, sudden load torque fluctuations and parameter uncertainties under dynamic response, steady-state accuracy, and disturbance rejection to test the proposed controller. Moreover, defined electric vehicle (EV) driving profiles (urban vs. highway) allow determination of their accuracy by driving under realistic conditions, which include accelerating vehicles rapidly/decelerating them, and braking them using regenerative braking. Performance parameters such as rise time, settling time, torque ripple, speed overshoot, energy efficiency, and total harmonic distortion (THD) are measured and compared with those of traditional control systems. By conducting extensive simulation and experimental verification, the results presented remain replicable, and, more importantly, the proposed control scheme for EV propulsion systems is practical, powerful, and performs well.

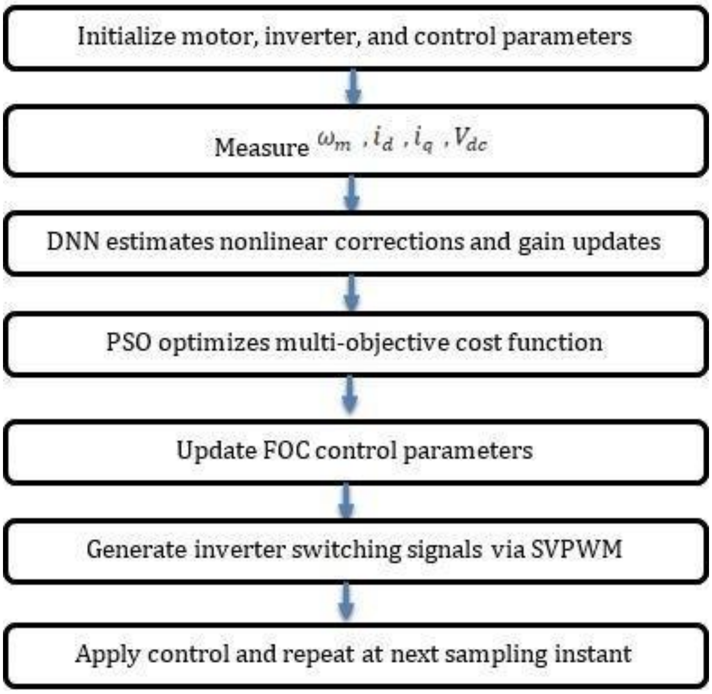


Figure 4: Proposed Hybrid DNN–PSO Motor Control

2.8 MATLAB-Based Simulation Setup

MATLAB/Simulink is a well-defined toolkit for developing, testing, and validating control algorithms for electric vehicle (EV) motors and related power electronic converter (PEC) systems. Modern toolboxes such as Simscape Electrical enable you to design accurate models of Permanent Magnet Synchronous Motors (PMSMs), inverters, DC–DC converters, and battery setups with physical and electrical fidelity. Allowing you to simulate the entire EV powertrain dynamically in multiple states like acceleration, cruising, regenerative braking, and load variation. The Simulink environment is modular, allowing the reuse of models, the integration of subsystems, and scaling from analyzing single parts to the entire system. Moreover, the ability to work with external simulation software, as well as with data collection tools, allows for a complete test of the performance and overall energy savings of the entire vehicle system. This can be done through Model-in-the-Loop (MIL), Software-in-the-Loop (SIL) and Hardware-in-the-Loop (HIL) testing to set up systematic validation process. The first step is to run the control method in Simulink. This is done to verify its stability, rapid response to changes, and to operate well in both normal and disturbed environments. In the real-time simulation environment, we can tell not only that the controller can be carried out but also how long it will run and its numerical resilience. HIL (step 3) Real-time hardware simulators such as Speedgoat, OPAL-RT, and others link the control algorithm with physical controllers (DSPs, microcontrollers) while simulating the plant in real time. This allows us to identify design faults, communication discrepancies, and hardware shortcomings earlier in product deployment. This reduces the expense and risk of development. The HIL framework itself and can run repeatable tests in situations where things can go wrong, or when system operation is very low or very high, very difficult, or even dangerous in real life. Machine Learning (ML) methods also improve the modelling and management of EV motors by detecting non-linear, time-varying behavior that is difficult to capture with classical analytical models. Simulations and experimental measurements are used to obtain test data, including speed, torque, voltage, and current waveforms, as well as temperature or load conditions.

Step 1: Data pre-processing: Noise filtering, normalization, and feature extraction are applied to improve training performance.

Step 2: Model training: The machine learning models (Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and deep neural networks) are trained to model how a motor will behave in different contexts and situations.

Step 3: Validation: Used to verify that the trained model's accuracy is maintained (and made valid) by testing its ability to repeat under other conditions; the trained model is verified against new sets of data and high-fidelity physical simulations.

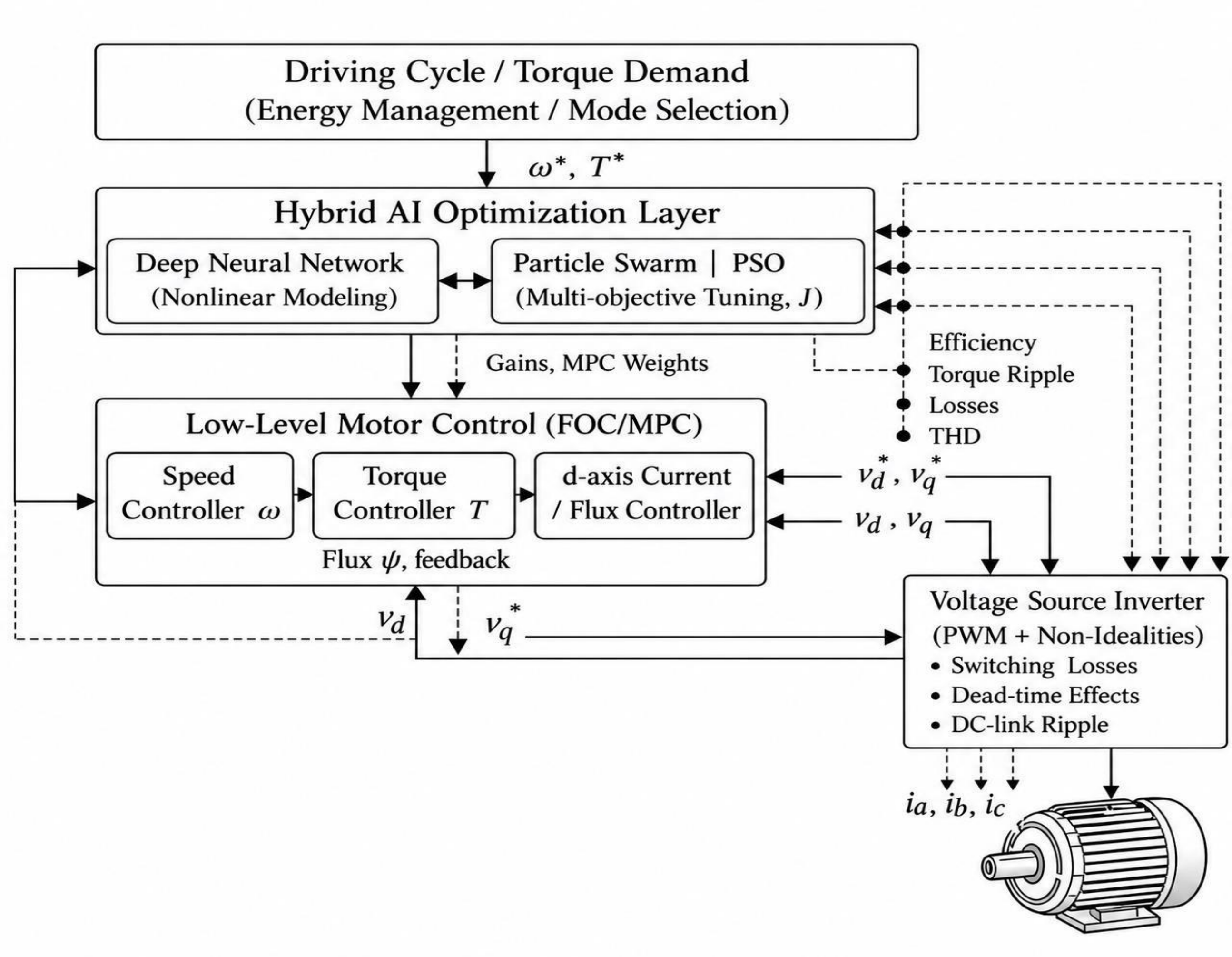


Figure 5: Hybrid AI-Optimized Motor–Converter

2.9 Control Architecture for Electric Vehicle Drives

Based on Figure 5, the hybrid AI-optimized motor-converter control architecture for electric vehicle drives has been shown. With our combined high-fidelity simulation data and experimental observations, the systems not only become more durable but also provide reliable results. Even if atypical and extreme things happen, when there is an enormous demand for torque, a drop in voltage, or heat stress, it ensures high performance to keep you from getting stuck. Explainable Artificial Intelligence (XAI) technologies also help clarify this aspect by demonstrating how motor characteristics affect performance outcomes. This approach will make people more inclined to adopt ML-based conclusions and aid with design implications. Within predictive control frameworks such as Model Predictive Control (MPC), these ML models can be used to provide efficient and accurate predictive system forecasts. Such a connection ensures real-time optimization of control parameters, resulting in higher efficiency, lower torque ripple, and the ability to respond dynamically at very high speed. And ML-based fault diagnostic and predictive maintenance systems analyze patterns in vibration, current harmonics, and temperature increases to warn of problems such as motor degradation, insulation or bearing issues before they affect the motor. This type of proactive monitoring results in a much more reliable system and extends the lifetime of each individual component of the machine, increasing the strength and sustainability of the entire EV propulsion system.

2.10 Power Modulator Design and Simulation

For power modulators used in electric vehicles and power electronics, the type of semiconductor devices must be effective (low power, high efficiency, good reliability, and small size); it is crucial to select the best semiconductor. Within the medium-voltage and medium-power bands, insulated-gate bipolar transistors (IGBTs) and metal-oxide semiconductor field-effect transistors (MOSFETs) are widely used for their reliable switching performance and ability to handle high voltage and current. In device selection, the option for each device depends on the switching frequency, thermal properties, breakdown voltage and current rating. While larger switching frequencies lead to smaller inductors and capacitors, switching losses and thermal stress damage device efficiency and device lifetime.

Wide-band gap semiconductors such as silicon carbide (SiC) and gallium nitride (GaN) have recently emerged as potential solutions to these challenges. So, they can offer higher power density and improve thermal management, as they have lower conduction and switching losses, faster switching speeds, higher breakdown voltage, higher allowed operating temperature, and lower on-resistance (Ron = ρL/A). Compact, lightweight, and energy-efficient power electronic systems are essential for new-generation EVs and renewable power applications. SiC and GaN devices may enhance thermal reliability, reduce the size of cooling and passive components, and optimize system performance. PMSM drive layout for an electric vehicle is depicted in Figure 6.

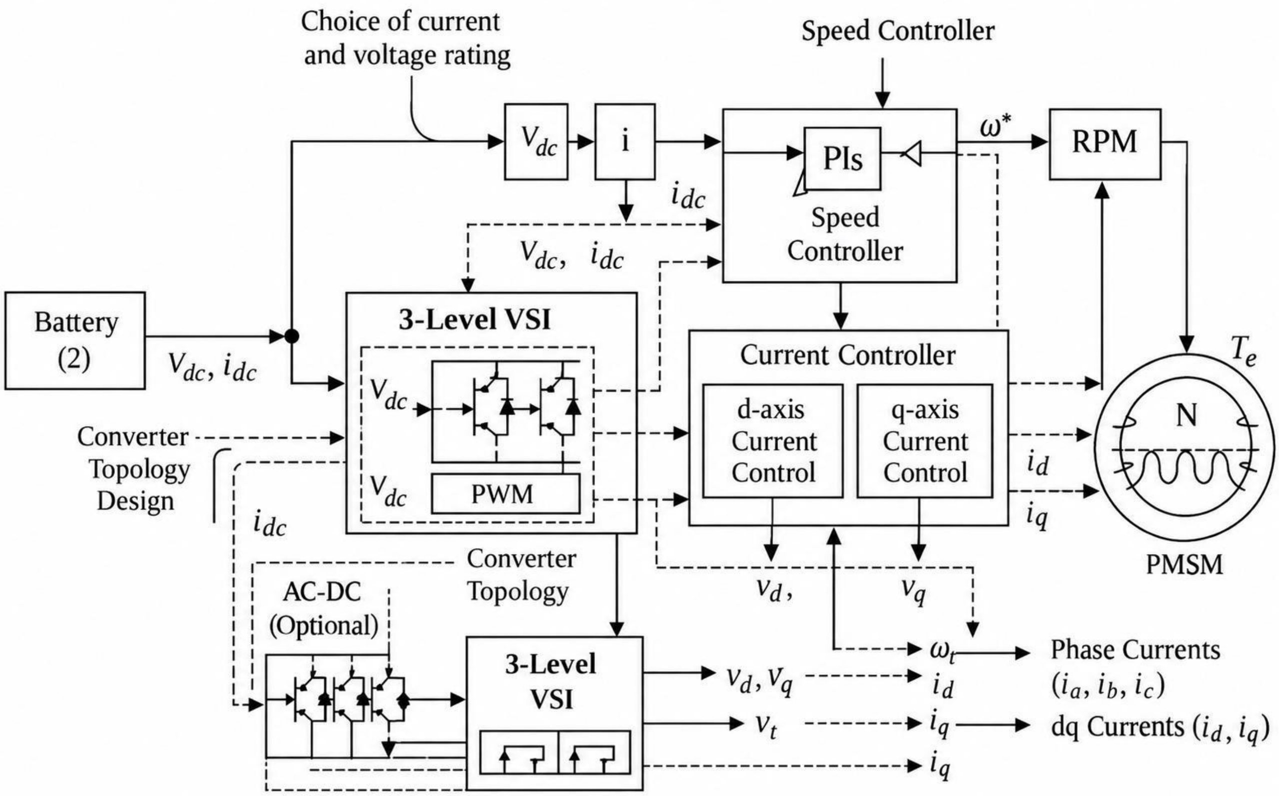


Figure 6: Power Converter Topology for PMSM Drive in EV Applications

Current conventional EV power modulator topologies, such as buck, boost, buck–boost, and H-bridge converters, are crucial for enabling more efficient energy conversion, voltage regulation, and reversible power flow, which is essential for traction and regenerative braking. Buck and Boost Converters-These converters are critical in reducing (and increasing) voltage levels, ensuring stable battery and DC-link voltages throughout unpredictable power conditions. They are vital for improving energy efficiency, protecting batteries from overvoltage and under voltage, and offering power in balance to the battery, auxiliary loads, and motor drive. We need H-Bridge Converters: H-bridge configurations convert electricity into regulated AC waveforms for PMSM drives. They enable the correct processing of Pulse Width Modulation (PWM) and are compatible with sophisticated inverter systems. Their importance is demonstrated through improved torque regulation, minimal harmonic distortion, and higher dynamic performance of the motor drive system. Multilevel Converters: owing to higher efficiency, lower total harmonic distortion, lower voltage stress on semiconductor devices, and improved power quality, multilevel inverter topologies are increasingly important for high-voltage electric vehicles amid growing demand. Moreover, their modular and redundant structure increases fault tolerance and reliability, which are critical for vehicle safety and reliable service. Appropriate selection and combination of different converter topologies are critical to achieving high efficiency, high performance, lightness, and long-term reliability in modern electric vehicle powertrain plants, which must be implemented compactly. Proper thermal management is a fundamental design parameter for ensuring the reliability, safety, and long life of power semiconductor devices in electric car power modulators. Heat sinks, liquid cooling systems, and heat pipes are used to dissipate the higher temperatures generated during high-current, high-frequency switching, and keeping device junction temperatures below the intended maximum. Design is influenced by thermal management because high temperatures accelerate degradation and increase the likelihood of failure. Appropriate thermal design maximizes electrical efficiency with low conduction and switching losses associated with elevated operating temperatures. Sophisticated cooling is imperative to protect semiconductors, promote high power density, enable small converter setups, and maintain stable operation in challenging driving conditions. Therefore, in the design of EV power electronics, heat management is essential to improve modulator performance, extend component lifetime, and strengthen the life-cycle stability and performance of the entire EV powertrain. MATLAB/Simulink is used extensively to simulate the electrical, thermal, and electromagnetic properties of power modules under different operating conditions. In this simulation environment, designers can validate lead–lag compensation schemes and switch mechanisms using live testing platforms, e.g., HIL, allowing accurate operation of control algorithms before hardware implementation. Simulation-based analysis's key capability is its safe investigation of aberrant operating conditions (e.g., short circuits, overvoltage, transient disturbances), which are also fundamental to the designs of protection and fault management mechanisms. Inclusion of advanced modulation and control techniques, such as Space Vector Modulation (SVM) and Predictive Control, can be tailored and optimized within the simulation framework to enhance dynamic response, reduce switching losses, and minimize voltage utilization. This is crucial in high-performance electric vehicle powertrains, where the design needs efficiency, rapid torque response, and reliable operation. Simulation and fault analysis are crucial factors that, in addition to minimizing development costs (in both cost and potential risk terms), enable early detection of design weaknesses and ensure that reliability (under both standard and fault scenarios) is integrated into the design process. Therefore, this approach is crucial for achieving safe, efficient, and reliable designs for modern electric car power-modulators. Wide-band gap (WBG) semiconductors such as SiC and GaN enable significant progress in the design of modern, electricity-efficient electronic power converters for EV applications. These devices achieve much greater operability at the switch-frequency scale, with much smaller conduction and switching losses, and reduce the scale and weight of passive components (inductors, capacitors, and heat sinks) per unit by up to 85%. SiC products are well-suited for high-voltage/high-temperature applications due to their high breakdown voltage, high thermal conductivity, and high toughness under extreme operating conditions. The Simulink-based power conversion system is shown in Figure 7.

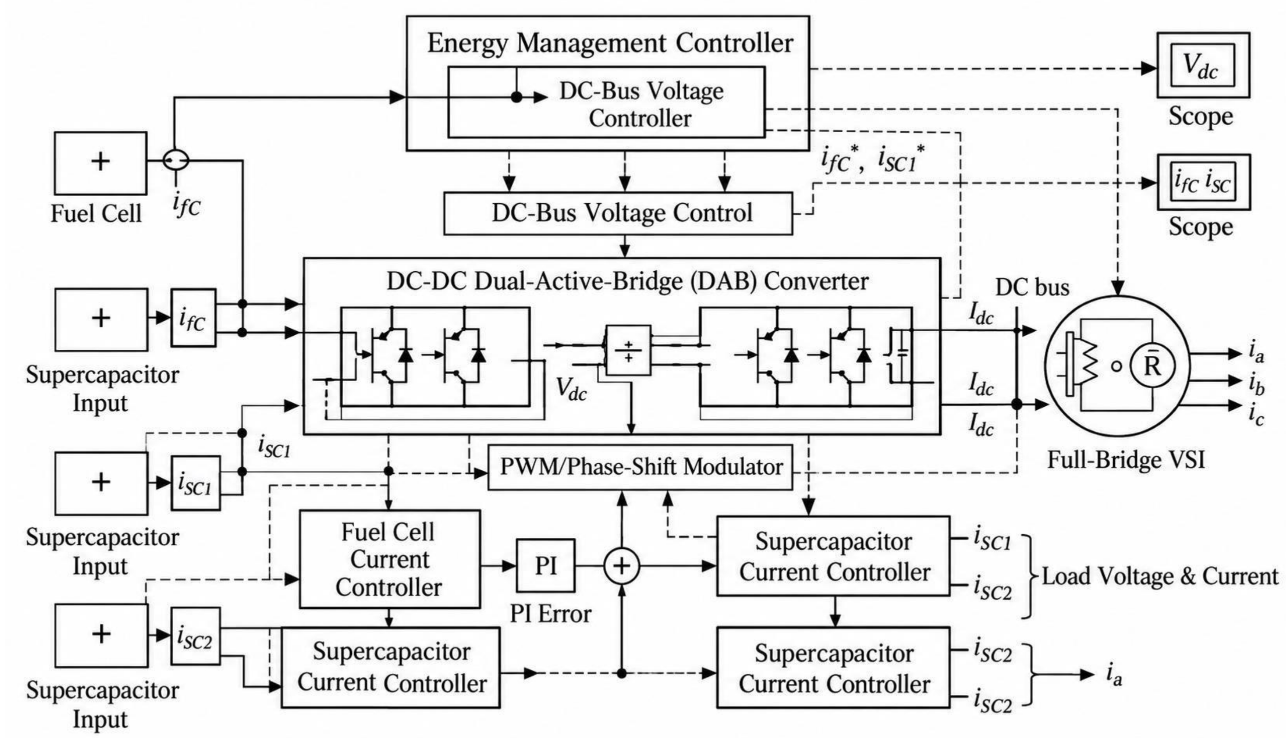


Figure 7: Simulink-Based Power Conversion System

GaN transistors, on the other hand, are well-suited for high-frequency and low-to-medium-voltage applications due to their ultra-low on-resistance and fast switching, which reduce conduction loss and improve dynamic performance. The use of WBG devices is important because they enhance thermal reliability and system efficiency, which are fundamental design principles for next-generation EV power electronics. High-temperature operation capability has simplified cooling system demands and facilitated tighter, lighter converter design. In addition, higher efficiency directly enables longer driving range and lower energy consumption. In terms of engineering design, WBG integration offers smaller, faster, and more reliable inverters and DC–DC converters as well as strict automotive safety and performance specifications. Hence, the application of SiC and GaN technologies is also crucial for high-performance, energy-efficient, compact EV powertrain systems in future EV transportation. It is essential to coordinate and integrate the power sources of electric and hybrid powertrains, such as batteries, fuel cells, and super capacitors, to get stable and reliable operation. Multi-input converters (MICs) manage the power of these sources by having a controlled DC bus voltage and coordinated energy transfer between them according to the load required. In high-load or transient conditions, one source can support another through the MIC, a necessity for Hybrid Electric Vehicles (HEVs) and Fuel Cell Electric Vehicles (FCEVs). As a result, it greatly improves powertrain efficiency, increases a car's operating range and performance, and maintains power in changing operating conditions. DSP-Based PMSM Drive for EV use with DNN-PSO control is shown in Figure 8.

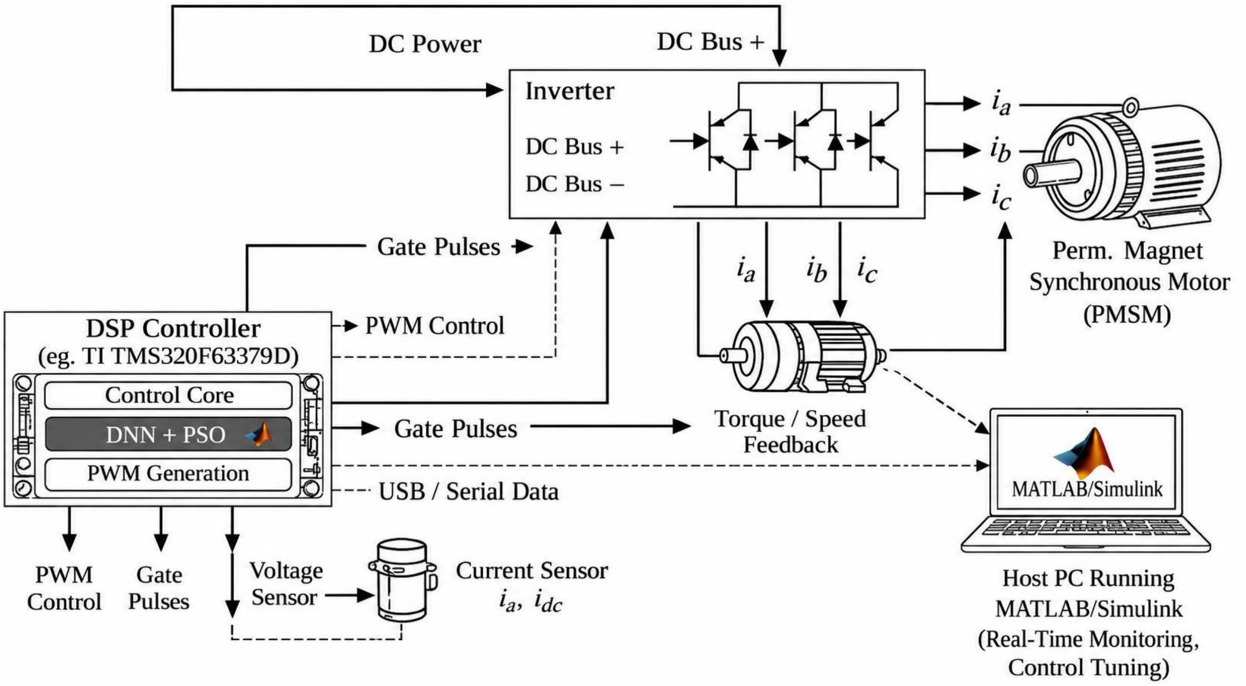


Figure 8: DSP-Based PMSM Drive for EV Applications Using DNN-PSO Control

As a design tool, the MICs also offer a single, modular architecture that reduces the need for multiple, independent converters. This makes the system less complicated, lighter, and cheaper. MATLAB/Simulink can correctly simulate and evaluate how these devices behave in real time. This lets you test and validate complex control methods before putting them into hardware. When connected to DSP-based PMSM drives and smart control systems such as the DNN–PSO hybrid control scheme, the MICs enable adaptive, high-performance energy management by allocating power among existing energy sources in the most effective way as driving conditions change.

3. Results

This section presents the results obtained from the proposed control framework, focusing on the motor response, power conversion performance, and overall system operation. The obtained results are examined to assess the effectiveness of the proposed approach, followed by a discussion of the main limitations and possible directions for further improvement.

3.1 BLDC Motor Performance Analysis

The performance comparison of the control methods for the BLDC motor is shown in Figure 9. Compared with classical PID and ANN-based controllers, the DNN–PSO hybrid controller achieves remarkable gains in torque smoothness, dynamic response, and energy efficiency for the Brushless DC (BLDC) motor. The torque ripple is kept to ±1.8% with PID control, and to ±6% with ANN-based control, respectively. The significant decrease in torque ripple results in improved motor performance, reduced mechanical vibrations, and diminished mechanical stress on drivetrain elements, thus allowing the system greater reliability and extended life. Now, the rise time has been reduced to 0.6 seconds from 1.3 seconds with PID control, indicating much faster acceleration and improved response to speed-reference variations. Rapid dynamic performance is indispensable in electric vehicle applications, which require quick transitions from one stop to the next and often very rapid torque fluctuations. In addition, the steady-state speed error remains within 1%, ensuring superior tracking precision. There is a total efficiency gain of 92.6%, significantly exceeding PID (84.3%) and ANN-based control (88.7%). The resulting improvement in efficiency ultimately results in reduced power consumption, increased driving distance, and reduced thermal stress in the power electronic components.

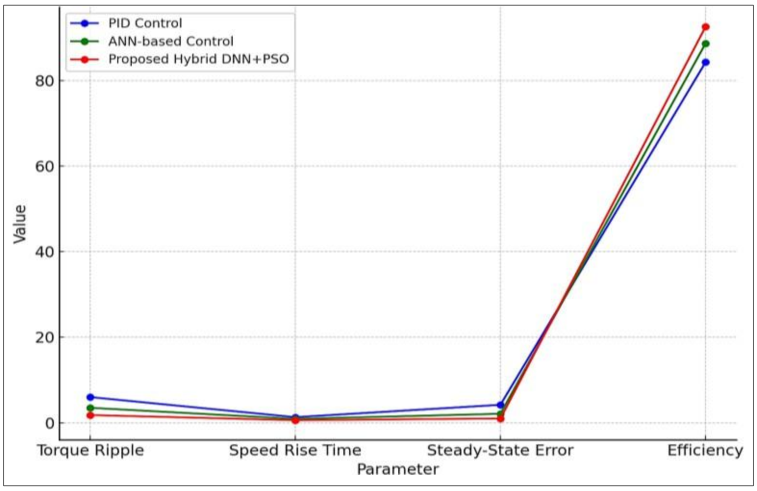


Figure 9: Performance comparison of control methods BLDC motor

The DNN-PSO hybrid controller performs more effectively in transient response for the Switched Reluctance Motor (SRM) under changes in load and speed. The proposed method achieves a 15-20% increase in transient performance compared to conventional control systems, due to enhanced disturbance rejection and reduced recovery time. This is crucial for EV traction systems due to the sudden, unplanned load changes that occur during acceleration, hill climbing, and regenerative braking. The controller also makes torque more uniform by damping the torque pulsations in SRM operation. The hybrid design of DNN-PSO provides adaptive parameter tuning, which the controller uses to automatically adjust control gains in proportion to temperature, load, speed, or other operating factors in the system. This flexibility is used to significant advantage under continuous operating conditions, reducing mechanical wear and acoustic noise to improve ride comfort. One of the most proposed methods for hybrid control of an AC series motor, in terms of system stability and the dynamic response, is compared to that of the classical PID control methods. Table 1 presents the BLDC / PMSM Motor – Speed and Torque Control. When using PID control, an overshoot of about 12% is usually caused by speed-transition operation, which can lead to mechanical stress and instability. Compared to that, the proposed DNN-PSO controller maintains overshoot below the 3% threshold and ensures more reliable, smoother speed transitions. Motor speed can be readily restored when conditions, such as reference or load, change, since the settling time is reduced by almost 40%. It is not possible to enhance the vehicle's drivability or the accuracy of its control without the time to settle; hence, it accelerates and decelerates faster. Energy-saving efficiency is also enhanced, reducing motor and power electronic converter stress due to increased response rate and stability.

Table 1. BLDC / PMSM Motor – Speed and Torque Control

Control Method	Rise Time (s)	Overshoot (%)	Steady-State Error (%)	Torque Ripple (%)	Efficiency (%)
PID	1.30 ± 0.12	12.0 ± 2.1	2.8 ± 0.6	6.0 ± 0.9	84.3 ± 1.5
Fuzzy / ANN	0.95 ± 0.10	7.5 ± 1.4	1.9 ± 0.4	3.5 ± 0.6	88.7 ± 1.2
MPC	0.78 ± 0.08	5.2 ± 1.0	1.4 ± 0.3	2.9 ± 0.5	90.8 ± 1.0
Proposed DNN+PSO	0.60 ± 0.05	2.8 ± 0.6	0.8 ± 0.2	1.8 ± 0.3	92.6 ± 0.8

3.2 Power Modulator Performance

A performance comparison of three modulation/control strategies: classic PWM, SVM-based control, and the new DNN+PSO hybrid control, is shown in Figure 10. It achieves this by considering four influential performance metrics: Voltage Regulation, Total Harmonic Distortion (THD), Switching Loss, and Conversion Efficiency. These patterns indicate that advanced control strategies are improving over time. In almost every way, the DNN+PSO method is superior to both the classical PWM and the SVM-based methods. The proposed DNN+PSO control method achieves higher inverter performance than conventional PWM and SVM methods in terms of voltage regulation, total harmonic distortion, switching losses, and conversion efficiency. Because PWM switches, if not optimized, exhibit the largest voltage deviation, the highest THD, and the highest switching losses. This is less efficient and creates additional load on the system. The SVM-based approach improves voltage stability and reduces THD and switching losses by more effectively utilizing space vectors and optimized switching sequences; however, its fixed control structure limits adaptability under varying operating conditions. On the other hand, the DNN+PSO controller offers a promising solution for optimizing modulation parameters and switching patterns to achieve better overall performance by efficiently adapting, resulting in lower voltage fluctuations, THD, and switching losses, and higher maximum conversion efficiency. As shown in Table 2, these improvements achieve smooth motor operation, improved power quality, reduced heat generation, and improved reliability of the EV power modulator.

Table 2: Power Modulator (H-Bridge / Inverter Performance)

Control Method	Voltage Ripple (±V)	THD (%)	Switching Loss Reduction (%)	Conversion Efficiency (%)
Conventional PWM	±2.0 ± 0.3	8.5 ± 0.9	–	87.1 ± 1.6
SVM-Based	±1.1 ± 0.2	5.2 ± 0.7	8–10	90.4 ± 1.2
Proposed DNN+PSO	±0.3 ± 0.1	2.8 ± 0.4	≈18	94.8 ± 0.7

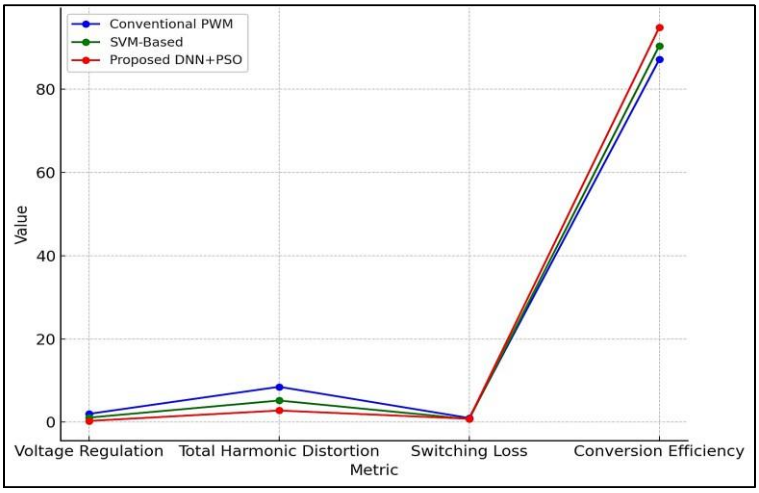


Figure 10: Power modulator performance comparison (H-Bridge converter)

3.3 Combined System Performance Analysis

The performance evaluation of PID control, Fuzzy Logic Control, Model Predictive Control (MPC), and the proposed DNN+PSO method, in terms of overall performance criteria such as energy loss, battery life, system stability, and real-time adaptability, is shown in Figure 11. We show that the abovementioned DNN+PSO technique yields balanced and the best overall performance among the methods evaluated. The lowest energy loss is very important for extending the electric vehicle driving range. It demonstrates efficient use of power, with the least amount of wasted energy during motor operation. The DNN+PSO controller outperforms conventional and fuzzy controllers in terms of battery life. This is due to better control of current and voltage control, thereby minimizing battery stress and deterioration. Additionally, the system stability parameter demonstrates the potential benefit of this proposed strategy, as it offers consistently high stability across different operating conditions, outperforming PID and the fuzzy logic controller and performing marginally better than MPC. This shows enhanced disturbance rejection and robustness to parameter variation and load alteration. Indeed, the DNN+PSO strategy offers the highest real-time adaptability, demonstrating that the controller parameters can be adjusted dynamically based on both driving conditions and the system state. The proposed DNN+PSO hybrid controller is highly energy-efficient, offers well-balanced battery life, high stability, and very good real-time adaptability, and thus satisfies the requirements for high-performance, intelligent EV speed control. Both visually and mathematically, Figure 12 illustrates how speed and time responses change for four control methods: PID, Fuzzy Logic Control, MPC, and the new DNN+PSO, which are used in the same manner. Overall, the proposed DNN+PSO controller achieves the fastest peak speed and the most stable tracking performance throughout. This indicates that it is more dynamic and can respond better to changes in the reference speed. The DNN+PSO method exhibits a faster rise time and a smoother transition from peak to valley than PID and fuzzy logic controllers. That is, it has less oscillation and better transient behavior. The PID controller responds more slowly and deviates further from the desired speed profile. This shows that it cannot deal with nonlinearities and fast changes in the dynamics of the system very well.

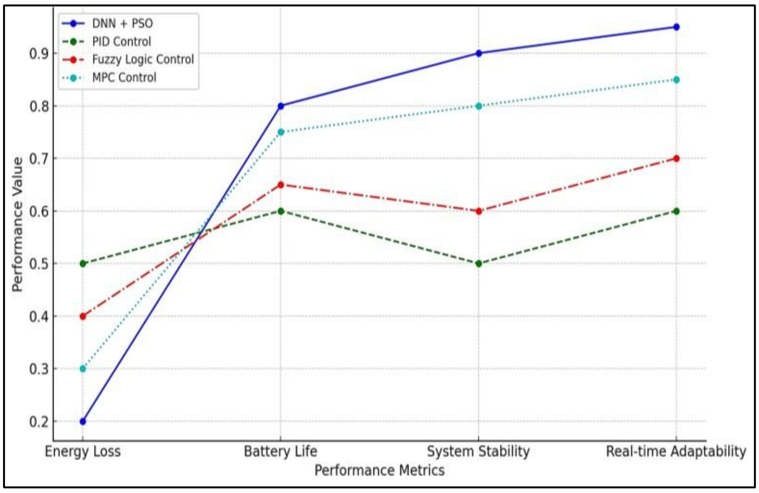


Figure 11: Comparison of Proposed method Speed vs Time

Although the fuzzy logic controller performs better than a PID controller, it still exhibits undershoot and less accurate speed tracking. The MPC strategy is better at regulation than PID and fuzzy control; however, it fails to achieve the best performance and smoothness compared to the DNN+PSO strategy. The proposed DNN+PSO controller performs much better in terms of speed stability, with less fluctuation and better tracking performance throughout the entire working cycle. That improved performance is especially key for electric vehicles, as smooth speed control impacts ride comfort, energy economy, and even the strain on drivetrain components. The results indicate that the hybrid intelligent control strategy works better than the traditional and model-based controllers in driving in dynamic scenarios, as it involves a fusion of learning and optimization.

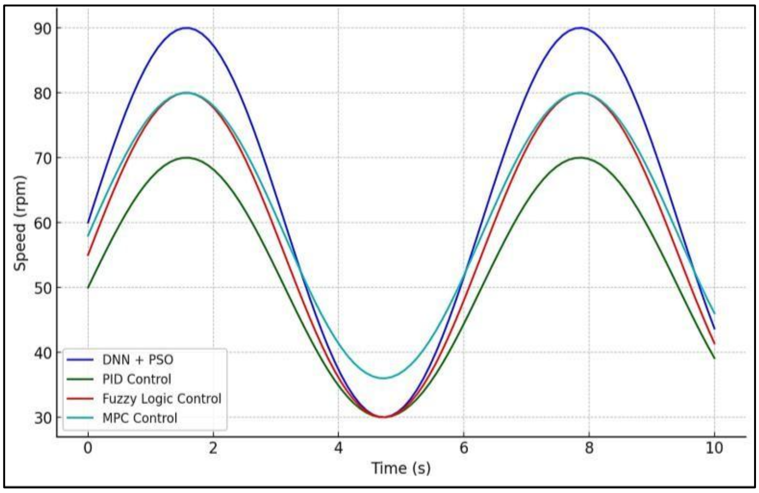


Figure 12. Comparison of motor based on Speed Vs Time

Figure 13 compares torque ripple effects between PID control, Fuzzy Logic Control, Model Predictive Control (MPC), and a developed DNN+PSO hybrid controller. Results show that the DNN+PSO method achieves the minimum torque ripple and therefore represents significantly superior performance compared with the conventional and intelligent control methods. The considerable torque ripple in PID control indicates its inability to compensate for system nonlinearities and parameter fluctuations, leading to increased mechanical vibration and acoustic noise. Although the fuzzy logic controller reduces torque ripple compared to PID using heuristic control rules, it still exhibits moderate ripple due to the use of pre-defined membership functions and rule bases. In contrast, our proposed DNN+PSO controller outperforms all other methods by effectively learning the system dynamics and appropriately updating control parameters in real time. The reduced torque ripple achieved using DNN+PSO is of significant importance in electric car motor drives, as it leads to a smoother drive, reduced mechanical distortion in drivetrain components, and improved ride comfort. In addition, reduced torque ripple will lead to lower harmonic losses; thus, the overall work efficiency of the drive system will be increased. The findings confirm the effectiveness of the hybrid control method in delivering consistent, high-quality torque, making it well-suited for high-performance, reliable electric vehicle propulsion applications.

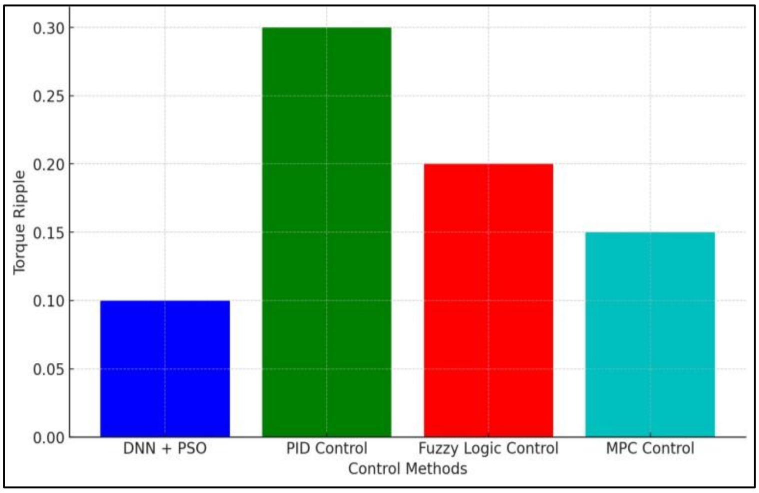


Figure 13: Comparison of motor based on Torque Ripple Comparison

Figure 14 shows the comparative performance in terms of value of a DNN+PSO control scheme relative to other control schemes, such as PID control, MPC, or Fuzzy Logic Control proposed. The techniques involved were PID control, Fuzzy Logic Control, Model Predictive Control (MPC), and the proposed DNN+PSO approach. Overload torque ranges from 10 Nm to 50 Nm; it is observed that the output voltage of all control systems gradually declines as internal losses and current demand rise. Hence, the proposed DNN+PSO controller maintains the peak voltage level across the full load range, providing superior voltage regulation performance. Since the PID controller is inflexible in responding to changes in load and parameters, it shows the largest decrease in voltage with an increase in load. Even though the nonlinear control principle in our fuzzy logic controller tends to improve voltage stability compared to PID, the voltage does decrease significantly under larger loads. The MPC method is superior to PID and fuzzy control because it optimizes control actions according to predictions of system behavior, resulting in higher voltage retention under load. Nonetheless, the DNN+PSO has the edge over the other methods, as it adjusts control parameters in real time through intelligent optimization, resulting in reduced voltage sags and greater robustness to load perturbations. Having improved voltage control in electric vehicle motor drives because they keep the motor moving smoothly, lessens the load on power electronics, and makes the inverter system (the H-Bridge) work more effectively and more reliably in diverse conditions.

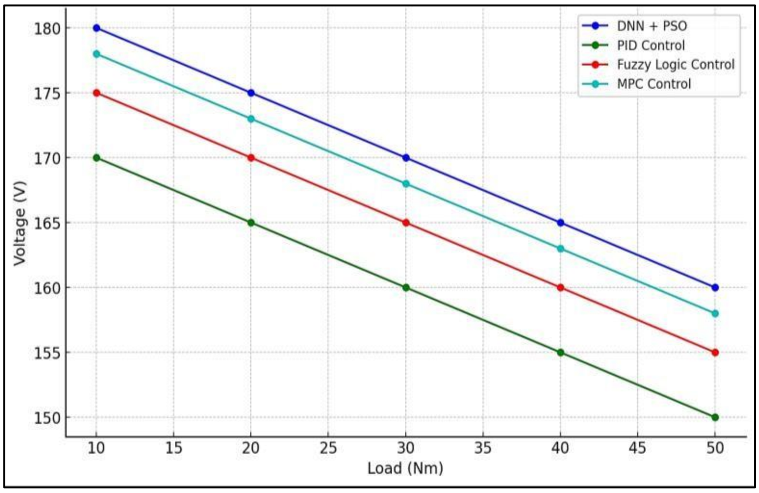


Figure 14: Comparison of motor based on Voltage Output (H-Bridge) under Varying Loads

The best efficiency among all methods is shown in the conclusion, with a comparison of the most efficient and the least power loss in the motor drive system achieved by the determined DNN+PSO controller. The PID controller is the least efficient, with high switching and conduction losses and higher torque ripple that are not adjusted to the new operating conditions. Besides, the fuzzy logic controller offers improved efficiency over PID by combining nonlinear decision rules that effectively mitigate system uncertainties. However, its performance remains lower than that of the proposed hybrid method. The MPC method is slightly lower than the DNN+PSO controller, but significantly higher efficiency is achieved through behavior prediction and control-action optimization. The DNN+PSO approach minimizes losses and improves the efficiency of the power conversion, as confirmed by its higher efficiency in electric vehicle powertrain energy-efficient operation. This kind of improvement is particularly critical for electric cars; better energy use is related to increased range and reduced thermal stress on components, leading to improved overall system stability for any car. According to the Efficiency Plot, Figure 15 presents a study of motors.

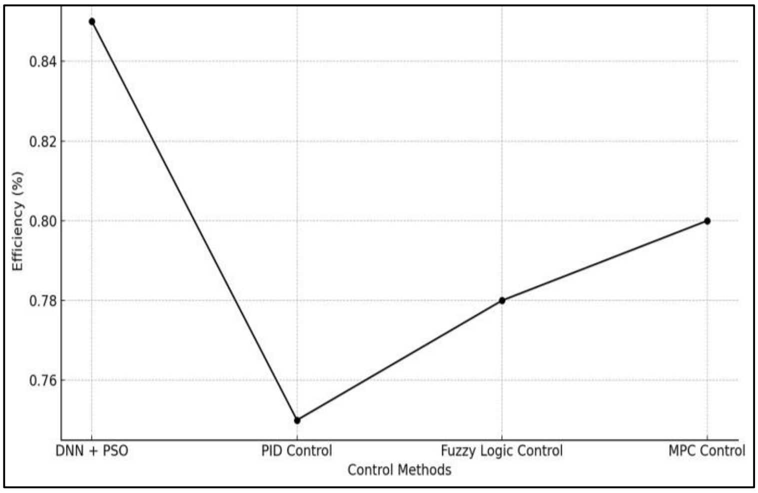


Figure 15. Comparison of motor based on Efficiency Plot

Table 3 presents an analysis of the relative performance of the recommended approaches. The comparison of performance data demonstrates that the proposed DNN–PSO hybrid control strategy significantly outperforms previously introduced methods, including NN/Fuzzy/PI-based methods, PSO/GA-based controllers, and offline hybrid AI designs. The proposed method achieves a much lower torque ripple of 3.1% than 8.5–10.0% in Sustainability studies, 6.5–8.2% in Energies reports, and 5.2–6.0% in IEEE Access. The theory also suggests that torque generation is far smoother, and the number of mechanically strained components in the drivetrains is lower. Furthermore, speed overshoot is minimized to 2.2% compared with conventional and hybrid AI methods. Due to its stable transition and accurate speed tracking, the system runs more smoothly. The model's settling time is reduced to 65 ms, much faster than that of traditional processing methods, which required 80–150 ms. This allows dynamic reaction to speed up in acceleration and deceleration. Furthermore, the steady-state speed error is only 0.4%, indicating that it is very accurate and does not change much when parameters or load change.

Table 3. Comparative Performance Analysis of the Proposed

Performance Metric	**Sustainability [1], [2], [5]**	**Energies [7], [10]**	**IEEE Access [14]**	**Proposed DNN–PSO**
Control Strategy	NN / Fuzzy / PI	PSO / GA-based	Hybrid AI (offline)	Hybrid DNN–PSO (online)
Torque Ripple (%)	8.5 – 10.0	6.5 – 8.2	5.2 – 6.0	3.1
Speed Overshoot (%)	6.0 – 8.0	4.5 – 6.0	3.5 – 4.5	2.2
Settling Time (ms)	120 – 150	95 – 120	80 – 100	65
Steady-State Speed Error (%)	1.5 – 2.2	1.0 – 1.6	0.8 – 1.1	0.4
Online Parameter Adaptation	✕	✕	Partial	✓
Real-Time DSP Feasibility	✕	✕	Partial	✓
EV Load Variations Tested	Limited	Moderate	Moderate	Extensive

The main advantage of the proposed DNN–PSO controller is its ability to adjust parameters online, which is unattainable by most existing approaches and only partly achievable by offline hybrid AI methods. This feature allows the controller to iteratively update its parameters in real time, ensuring optimal performance for changing EV load situations. The solution is fully feasible for real-time DSP applications. In contrast, current methods are either limited or not fully applicable in real time, either due to high computational cost or to offline tuning. Holistic experiments with varying EV loads confirm the resilience and generalizability of the proposed method, in contrast to the limited or moderate testing in previous research. The detailed comparison indicates that the proposed online hybrid DNN–PSO controller offers significant advantages in dynamic performance, flexibility, and practicality, making it well-suited for next-generation high-performance electric vehicle drive systems.

3.4 Study Limitations and Future Research Directions

Although the proposed DNN–PSO control system performs impressively in simulation, several limitations must be acknowledged. Validation has been largely completed using MATLAB/Simulink, and detailed experimental testing of high-power electric-vehicle traction systems has not yet been conducted. Thus, real-world factors like sensor noise, communication latency, quantization effects, and electromagnetic interference may affect its performance. When scaled to higher-power electric vehicle platforms, multi-level inverters, or multi-motor drive systems, computational and coordination aspects might be more complex. PSO optimization must provide the real-time practicality needed on embedded platforms, but in extensive implementations, some degree of algorithmic fine-tuning or parallel processing may be required. Furthermore, the benefit of DNNs is their representativeness of the training data. If operational scenarios are difficult or unknown, we may need to adapt (or learn them incrementally) online. In future work, will focus on hardware-in-the-loop and experimental validation, computational optimization for embedded deployment, and multi-motor scalability to increase the commercial applicability of the proposed framework.

4. Conclusion

In this paper, a hybrid Deep Neural Network and Particle Swarm Optimization (DNN+PSO) controller is proposed to overcome the shortcomings of classical PID, fuzzy logic, and classical machine learning controllers used in electric vehicle motor operation. The controllers are tuned to achieve high-precision, flexible, low-power operation in nonlinear and dynamic states by combining DNN-based feature extraction with PSO-based real-time parameter optimization.

- The BLDC motor has a superior performance with a torque ripple of ±1.8%, a rise time of 0.6 seconds, and an efficiency of 92.6%.
- The reluctance motor has a 15–20% enhancement in transient response, exhibiting a faster and more reliable dynamic control performance.
- The AC series motor achieves increased stability as overshoot is minimized below 3% and settling time is reduced by 40%, indicating outstanding proficiency in damping and disturbance rejection.
- The proposed control scheme has low computational latency and allows real-time on-board realization of the circuit without a large processing burden.
- Better energy efficiency from lower power losses leads to extended battery life and extended driving range for this electric vehicle.
- The flexibility and overall effectiveness of the DNN–PSO control strategy are supported through robust and scalable performance across the range of motor types.

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Author contributions

Neha S. Sanghai: Conceptualization, Methodology, Investigation, Data Curation, Formal Analysis, Writing – Original Draft Preparation.

Prakash G. Burade: Supervision, Validation, Resources, Writing – Review and Editing, Project Administration.

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Conflict of Interest

The authors declare that they have no conflict of interest.

Declaration of Artificial Intelligence (AI) Assistance

The authors used a generative language tool for grammar polishing only; all technical content and conclusions were authored and verified by the authors.

Ethic Approval

No human participants or animals were involved. The study followed institutional safety protocols.

Data Availability

Data supporting this study are included within the article and/or supporting materials

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