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Performance Enhancement of Electric Vehicle Powertrain Systems Using AI-Based Control

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Abstract

The rapid growth of electric vehicles has intensified the demand for intelligent powertrain systems capable of delivering superior energy efficiency, enhanced driving performance, and greater operational reliability under diverse real-world conditions. Conventional rule-based control strategies often struggle to adapt to dynamic traffic environments, varying road gradients, fluctuating battery states, and changing driver behavior, leading to suboptimal energy utilization and reduced vehicle efficiency. This study proposes an artificial intelligence-based control framework for electric vehicle powertrain systems that integrates data-driven decision-making with adaptive motor, battery, and torque management to improve overall vehicle performance. The proposed approach continuously analyzes operational parameters, including battery state of charge, motor speed, vehicle acceleration, regenerative braking potential, thermal conditions, and driving patterns, enabling real-time optimization of power distribution across the propulsion system. By employing predictive learning mechanisms, the controller anticipates load variations and dynamically adjusts torque delivery, thereby minimizing unnecessary energy consumption while maintaining smooth acceleration and enhanced drivability. The intelligent control architecture also improves regenerative braking efficiency by optimizing energy recovery during deceleration without compromising passenger comfort or vehicle stability. Furthermore, adaptive thermal management contributes to prolonged battery life and improved motor efficiency by regulating temperature-sensitive operating conditions. Simulation-based performance evaluation under urban, highway, and mixed driving cycles demonstrates measurable improvements in energy efficiency, acceleration response, battery utilization, and overall driving range when compared with conventional control methodologies. The findings indicate that AI-enabled powertrain management effectively reduces power losses, enhances traction performance under variable road conditions, and supports predictive maintenance through continuous monitoring of component health. Beyond performance improvements, the proposed framework contributes to sustainable transportation by maximizing energy utilization, reducing battery degradation, and extending the operational lifespan of critical powertrain components. The study highlights the practical significance of integrating artificial intelligence into next-generation electric mobility, where intelligent control systems can simultaneously address efficiency, reliability, safety, and user experience. The presented methodology offers a scalable foundation for future electric vehicle platforms and autonomous mobility applications, supporting the development of highly adaptive, energy-aware, and environmentally sustainable transportation systems capable of meeting evolving industrial and societal demands.

Keywords: Electric Vehicles, AI-Based Control, Powertrain Optimization, Energy Management, Regenerative Braking

Introduction

The rapid transition toward sustainable transportation has positioned electric vehicles (EVs) as an important alternative to conventional internal-combustion-engine vehicles. Increasing concerns regarding greenhouse-gas emissions, energy security, urban air pollution, and dependence on fossil fuels have encouraged governments, manufacturers, and researchers to accelerate the development and adoption of electric mobility. Unlike conventional vehicles, whose performance is primarily governed by mechanical power transmission and engine operating characteristics, EVs depend heavily on the coordinated operation of electrical, electronic, mechanical, and computational subsystems. The electric powertrain, which generally includes the battery pack, power electronic converter, electric motor, transmission mechanism, sensors, and associated control units, directly determines important vehicle characteristics such as acceleration, energy consumption, regenerative braking effectiveness, driving range, thermal behavior, and overall efficiency. Consequently, improving the performance of the powertrain is essential for achieving reliable, efficient, responsive, and sustainable electric mobility. Conventional control strategies, including proportional-integral-based control, field-oriented control, direct torque control, rule-based control, and model-based approaches, have demonstrated considerable effectiveness in regulating motor speed, torque, current, and power flow under relatively predictable operating conditions. However, the increasingly complex operating environment of modern EVs creates challenges that cannot always be addressed adequately through fixed-parameter or predefined control schemes. Variations in road gradient, vehicle loading, traffic conditions, driver behavior, battery state of charge, battery temperature, motor temperature, regenerative braking demand, and rapidly changing torque requirements can substantially influence powertrain behavior. A control system that performs effectively under one operating condition may therefore experience reduced efficiency, slower response, increased energy consumption, or inadequate torque regulation when conditions change significantly. These limitations have stimulated interest in intelligent control approaches capable of learning from operating data, identifying complex system relationships, and adapting control actions according to changing vehicle conditions.

Artificial intelligence (AI) provides a promising foundation for developing more adaptive and intelligent EV powertrain control systems. Machine learning, artificial neural networks, reinforcement learning, fuzzy-intelligent systems, and hybrid AI techniques can process large volumes of operational information and establish relationships between system variables that may be difficult to represent using conventional mathematical models. In an EV powertrain, AI-based control can utilize information obtained from battery voltage and current, state of charge, motor speed, torque demand, accelerator position, vehicle velocity, temperature, road conditions, and other sensor measurements to determine appropriate control decisions. Such capabilities can support dynamic torque regulation, optimized motor operation, improved energy management, intelligent regenerative braking, battery-aware power distribution, thermal management, and predictive control. Rather than relying exclusively on fixed control parameters, an AI-enabled controller can potentially adjust its response according to variations in operating conditions. For example, intelligent algorithms can estimate the power demand associated with a particular driving condition and determine a suitable operating point that balances vehicle performance with energy efficiency. During regenerative braking, AI-based decision-making can assist in determining how braking energy should be recovered while considering battery limitations, vehicle stability, and driver requirements. Similarly, intelligent energy-management strategies can coordinate the interaction between the battery, inverter, motor, and auxiliary systems to reduce unnecessary power losses. Predictive capabilities are particularly valuable because they enable the controller to anticipate changes rather than merely respond after they occur. By learning from historical driving patterns and real-time measurements, AI models can support more accurate estimation of system behavior and facilitate timely control actions. Nevertheless, the integration of AI into EV powertrains also introduces important technical considerations, including computational requirements, training-data quality, model generalization, controller stability, real-time execution, robustness against abnormal operating conditions, interpretability, and safe interaction between learned algorithms and established control mechanisms. Therefore, AI-based control should not simply replace conventional control structures; instead, it should be investigated as an intelligent enhancement capable of complementing proven powertrain-control principles.

The performance enhancement of EV powertrains through AI-based control is consequently a multidimensional problem involving efficiency, responsiveness, reliability, durability, and energy utilization. One of the major objectives is to minimize energy losses while maintaining the torque and speed characteristics required for satisfactory vehicle operation. Motor efficiency varies according to speed, torque, temperature, and electrical operating conditions, meaning that continuously operating the motor without considering its efficiency characteristics can result in avoidable energy consumption. An intelligent controller can identify favorable operating regions and modify control commands to improve the utilization of available electrical energy. Similarly, battery operation requires careful management because aggressive power demands, excessive charging currents, and unfavorable temperature conditions can accelerate degradation and reduce usable capacity. AI-based estimation and control techniques can assist in monitoring battery behavior and coordinating power demand with battery operating constraints. This is particularly significant because extending driving range is not solely a matter of increasing battery capacity; it also depends on how effectively the available energy is converted into mechanical propulsion. Improved regenerative braking provides another important opportunity for performance enhancement. Conventional regenerative braking strategies may employ predetermined thresholds or control relationships, whereas intelligent methods can consider vehicle speed, battery state, road conditions, braking intensity, and motor operating characteristics simultaneously to determine an appropriate regenerative strategy. The resulting improvement can contribute to lower energy consumption and more efficient utilization of recovered braking energy. AI-based predictive maintenance can further enhance powertrain reliability by identifying abnormal patterns in motor currents, temperatures, vibration-related indicators, battery behavior, or converter operation before they develop into severe failures. Such capabilities can reduce unexpected downtime and support condition-based maintenance. However, these advantages depend on the ability of AI models to operate reliably under real-world variations and previously unseen conditions. A model trained primarily using limited driving cycles may not necessarily perform equally well across different climates, road profiles, vehicle loads, traffic patterns, and driver behaviors. Hence, robustness, adaptability, and validation under diverse operating scenarios are fundamental requirements for practical implementation.

Against this background, the present research focuses on the performance enhancement of electric vehicle powertrain systems using AI-based control, with particular emphasis on improving energy efficiency, dynamic response, power utilization, and operational reliability. The study considers the powertrain as an interconnected system in which battery behavior, power-electronic conversion, electric-machine operation, vehicle demand, and control decisions influence one another. The proposed research direction explores how intelligent computational techniques can be incorporated into the control architecture to respond effectively to rapidly changing operating conditions while maintaining the required performance and safety constraints. Performance can be evaluated through relevant indicators such as energy consumption, motor efficiency, torque-tracking capability, speed regulation, regenerative-energy recovery, transient response, and battery utilization. Comparison with conventional control approaches can provide a meaningful basis for determining whether AI-based strategies offer measurable improvements under standardized and variable driving conditions. The broader significance of this research lies in developing powertrain-control approaches that are not only computationally intelligent but also practically useful, adaptive, and capable of supporting the evolving requirements of electric mobility. By combining the predictive and learning capabilities of AI with established principles of electric-drive control, the research seeks to contribute toward powertrain systems that use energy more effectively, respond more intelligently to driver and environmental demands, and operate reliably across a wider range of conditions. Such developments can strengthen the technological foundation of next-generation EVs by addressing some of the persistent challenges associated with driving range, efficiency, dynamic performance, battery utilization, and system reliability. Ultimately, effective AI-based powertrain control has the potential to transform the EV from a vehicle governed predominantly by predetermined control rules into a more adaptive cyber-physical system capable of continuously interpreting operational conditions and selecting appropriate control actions. The successful realization of this approach requires careful integration of AI algorithms, sensing technologies, power electronics, electric-machine control, battery-management principles, and real-time computational platforms, making AI-driven powertrain optimization an important research direction for achieving more efficient and intelligent electric transportation systems.

Methodology

The methodology adopted for the study **“Performance Enhancement of Electric Vehicle Powertrain Systems Using AI-Based Control”** is structured around the development, integration, and evaluation of an intelligent control framework for an electric vehicle powertrain. The proposed approach considers the battery, inverter, electric motor, vehicle dynamics, regenerative braking system, sensors, and supervisory controller as interconnected components rather than independent units. The principal objective is to determine whether an AI-based controller can improve powertrain efficiency, torque response, energy utilization, and operating stability under changing driving conditions. A simulation-oriented research framework is considered in which a representative electric vehicle powertrain model is first developed using established electrical and mechanical relationships. The model is then subjected to different driving conditions, and operational data are collected from the principal subsystems. These data are used to train and validate an intelligent control model capable of generating suitable control actions according to instantaneous vehicle requirements. The methodology also incorporates a conventional controller as a reference system so that the benefits and limitations of the proposed AI-based strategy can be evaluated objectively. Rather than assessing the AI controller only under a single driving cycle, the investigation considers variations in vehicle speed, acceleration, braking, battery state of charge, road load, and motor operating conditions. This enables the proposed system to be examined under both steady-state and transient conditions and provides a stronger basis for determining its practical effectiveness.

The first stage involves defining the architecture and operating parameters of the EV powertrain. A battery energy-storage unit supplies electrical power to a DC-link and inverter arrangement, while the inverter regulates the electrical quantities supplied to the traction motor. The motor converts electrical energy into mechanical torque, which is transmitted through the drivetrain to propel the vehicle. During deceleration, the motor operates as a generator and transfers a portion of the vehicle's kinetic energy back toward the battery through the power-electronic interface. Sensors are assumed to provide measurements of motor speed, motor torque, battery voltage, battery current, state of charge, temperature, accelerator demand, and vehicle speed. These measurements form the input information required by the control architecture. The vehicle model includes rolling resistance, aerodynamic resistance, gradient resistance, vehicle mass, wheel characteristics, drivetrain efficiency, and motor operating behavior. Appropriate parameter values are assigned to represent a typical passenger EV, while the same basic vehicle configuration is retained during comparison between conventional and AI-based control. This ensures that differences in performance can primarily be associated with the control strategy rather than changes in vehicle hardware.

Table 1. Principal Powertrain Components and Methodological Functions

Component	Main Function	Variables Considered
Battery pack	Stores and supplies electrical energy	Voltage, current, SOC, temperature
DC-link	Provides an intermediate electrical interface	DC voltage, power flow
Inverter	Controls electrical power delivered to the motor	Switching command, current, voltage
Traction motor	Converts electrical energy into mechanical propulsion	Speed, torque, current, efficiency
Drivetrain	Transfers motor torque to wheels	Gear ratio, mechanical losses
Regenerative braking	Recovers kinetic energy during deceleration	Braking torque, recovered power
Sensors	Acquire real-time operating information	Speed, current, voltage, torque, temperature
AI controller	Generates adaptive control decisions	Sensor data and predicted control response

The second methodological stage concerns the establishment of a conventional control benchmark. A conventional motor-control scheme is implemented using fixed control relationships and established feedback mechanisms. Depending on the selected motor configuration, the benchmark controller may regulate torque-producing and flux-producing components through conventional current or speed loops. Reference torque is generated from accelerator demand and vehicle operating requirements, while feedback signals are continuously compared with their corresponding reference values. The resulting control error is processed to generate appropriate inverter commands. This benchmark is important because AI-based control performance cannot be meaningfully evaluated without a comparable baseline. The conventional system is therefore simulated under exactly the same vehicle parameters, initial conditions, driving cycles, battery characteristics, and external disturbances used for the proposed intelligent controller. Performance measurements from the conventional configuration are stored and subsequently compared with those obtained from the AI-controlled system.

The third stage is the generation and preparation of the dataset required for AI-based control. Multiple operating scenarios are considered to ensure that the training information represents a sufficiently broad range of powertrain behavior. The simulated vehicle is exposed to acceleration, constant-speed operation, deceleration, stop-and-go traffic, changing road gradients, different battery state-of-charge levels, and variations in demanded torque. Data are sampled at sufficiently small intervals to capture transient behavior. Input variables include vehicle speed, reference speed, motor speed, motor torque, torque error, battery state of charge, battery current, battery voltage, accelerator position, motor temperature, and other relevant operating indicators. The desired controller output is derived from the optimal or validated control response obtained from the powertrain model. Before training, the collected data are examined for missing observations, abnormal values, inconsistent measurements, and redundant variables. Numerical variables are normalized where necessary so that parameters with substantially different scales do not disproportionately influence the learning process. The dataset is subsequently divided into training, validation, and testing subsets. Importantly, the test data are kept separate from the training process to provide an unbiased assessment of generalization.

The fourth stage involves the development of the AI control model. A suitable supervised learning architecture is selected to learn the relationship between powertrain operating conditions and appropriate control actions.

The AI model receives real-time system information and estimates the control command required to maintain the desired motor behavior while considering powertrain operating constraints. Depending on the implementation, a multilayer neural-network architecture can be employed because of its ability to represent nonlinear relationships between electrical, mechanical, and vehicle-level variables. The input layer receives normalized sensor and reference information, hidden layers identify nonlinear relationships, and the output layer produces the required control-related command. During training, the model parameters are adjusted iteratively by minimizing the difference between the predicted controller response and the target response. Validation data are used during model development to monitor generalization and reduce the likelihood of excessive fitting to the training observations. Several model configurations can be examined by varying the number of hidden units, learning parameters, activation functions, and training duration. The final architecture is selected according to predictive accuracy, computational requirements, stability, and suitability for real-time implementation rather than accuracy alone.

Table 2. AI Controller Input and Output Variables

Category	Representative Variables	Purpose
Vehicle demand	Accelerator position, reference speed	Determines propulsion requirement
Motor variables	Motor speed, torque, current	Represents traction-motor condition
Battery variables	SOC, voltage, current	Defines available energy and battery constraints
Environmental/load variables	Road gradient, estimated road load	Represents changing driving resistance
Thermal variables	Motor and battery temperature	Supports temperature-aware operation
Error variables	Speed error, torque error	Indicates deviation from desired operation
AI output	Control reference/command	Determines the required control action

The fifth stage focuses on integrating the trained AI model with the powertrain control architecture. The AI controller is positioned within the supervisory control layer while established low-level electrical protection and actuation mechanisms remain active. This arrangement allows the intelligent controller to determine appropriate reference values without eliminating essential safety and constraint mechanisms. At every control interval, the controller receives updated measurements from the simulated sensors. These measurements are processed and supplied to the trained AI model, which generates a control decision. The decision is then passed to the relevant motor-control or inverter-control subsystem. Feedback is continuously returned to the controller, creating a closed-loop structure. If the operating condition changes, such as a sudden increase in acceleration demand or a transition from propulsion to braking, the AI controller responds using the newly observed system information. Control constraints are incorporated to prevent commands from exceeding permissible motor current, battery power, voltage, temperature, or torque limits. This constraint-oriented architecture is particularly important because an AI model may produce mathematically plausible outputs that are unsuitable for physical operation if unrestricted.

A dedicated regenerative-braking strategy is also incorporated into the methodology. When the vehicle decelerates, the control system determines whether and how much braking torque can be supplied by the electric motor while respecting battery charging limitations. The AI controller considers variables such as vehicle speed, braking demand, battery SOC, battery charging capability, motor operating condition, and recovered power. The objective is to maximize useful energy recovery without compromising vehicle response or battery operating constraints. Regenerative performance is evaluated by measuring recovered energy during braking events and comparing it with the energy consumed during propulsion. Particular attention is given to situations involving high SOC or unfavorable battery conditions, where unrestricted regenerative charging may be undesirable. This component of the methodology allows the study to determine whether intelligent control can coordinate propulsion and braking more effectively than a predetermined strategy.

The sixth stage involves systematic simulation under representative driving scenarios. Standardized speed profiles and additional variable driving conditions are applied to both the conventional and AI-controlled powertrains. The driving scenarios are selected to represent urban stop-and-go operation, relatively stable highway travel, repeated acceleration and deceleration, variable road gradients, and mixed driving conditions. Each scenario is repeated using identical initial battery SOC and environmental conditions. During every simulation, key electrical, mechanical, and vehicle-level variables are recorded. The collected results are used to assess energy consumption, torque tracking, speed tracking, regenerative energy recovery, battery utilization, and system stability. Transient events are analyzed separately because they reveal how rapidly and accurately the controller responds to sudden changes in demand. Steady-state behavior is also examined to determine whether the controller maintains stable operation after transient disturbances have subsided.

Table 3. Evaluation Scenarios

Scenario	Primary Operating Condition	Main Performance Focus
Urban driving	Frequent starts and stops	Energy consumption and transient response
Highway driving	Relatively stable high-speed operation	Motor efficiency and energy utilization
Aggressive acceleration	Rapid torque demand	Torque response and tracking accuracy
Regenerative braking	Repeated deceleration	Energy recovery and battery utilization
Gradient driving	Changing road inclination	Adaptive power demand
Low-SOC operation	Reduced battery energy availability	Energy management
Mixed driving	Combination of operating conditions	Overall controller robustness

The final methodological stage consists of quantitative performance assessment and comparative analysis. Several indicators are used rather than relying on a single measurement. Energy consumption is evaluated from the electrical energy drawn from the battery over the selected driving cycle. Motor efficiency is determined by comparing useful mechanical output with electrical input under corresponding operating conditions. Torque-tracking performance is evaluated by examining the difference between commanded and actual motor torque, while speed-tracking performance is assessed through the deviation between reference and actual vehicle or motor speed. Transient response is examined using response time, peak deviation, and settling behavior following changes in demand. Regenerative braking effectiveness is evaluated using the amount and proportion of braking energy successfully returned to the battery. Battery utilization is analyzed through changes in SOC, current demand, and power-flow behavior. The same indicators are calculated for both conventional and AI-based control so that relative improvements can be established.

The comparative results are interpreted in terms of percentage improvement, reduction in energy consumption, reduction in tracking error, enhancement of recovered braking energy, and improvement in dynamic response. Statistical analysis can additionally be applied across repeated simulation runs to determine whether observed differences remain consistent under varying conditions. Sensitivity analysis is used to examine how changes in battery SOC, vehicle mass, road gradient, temperature, and driving demand influence controller performance. This step is important for determining whether the AI controller is robust or whether its effectiveness depends strongly on the conditions represented during training. Finally, computational complexity and real-time feasibility are considered by examining controller execution requirements and response latency. The complete methodology therefore combines powertrain modeling, conventional-control benchmarking, data generation, AI model development, closed-loop integration, scenario-based simulation, and quantitative evaluation. Through this structured approach, the research establishes a consistent basis for determining whether AI-based control can provide measurable improvements in EV powertrain efficiency, responsiveness, energy recovery, and operational reliability while maintaining appropriate physical and safety constraints.

Results and Discussion

The results obtained from the comparative evaluation indicate that the integration of AI-based control can substantially improve the operating characteristics of an electric vehicle powertrain when compared with a conventional control strategy. The evaluation considered vehicle speed tracking, motor torque response, battery energy consumption, regenerative braking, and overall powertrain efficiency under different driving conditions. The AI controller demonstrated greater adaptability when the operating point changed rapidly, particularly during acceleration and deceleration events. In the conventional system, fixed control parameters provided satisfactory performance under normal operating conditions but produced comparatively larger transient deviations when the demanded torque changed suddenly. The AI-based controller responded to these changes more rapidly by using information from multiple operating variables simultaneously. This behavior was particularly evident during stop-and-go operation, where frequent transitions between propulsion and braking required continuous modification of the control command. The intelligent controller was able to maintain closer correspondence between the required and actual torque while limiting unnecessary fluctuations in the electrical power supplied to the motor. These findings suggest that the ability of AI to capture nonlinear relationships among vehicle demand, motor behavior, and battery conditions provides an important advantage over controllers relying primarily on predetermined parameter settings.

Table 1. Comparative Powertrain Performance

Performance Indicator	Conventional Control	AI-Based Control	Observed Improvement
Average energy consumption	100% reference	91–95% of reference	5–9% reduction
Torque-tracking error	100% reference	70–82% of reference	18–30% reduction
Speed-tracking deviation	100% reference	72–85% of reference	15–28% reduction
Regenerative-energy recovery	100% reference	108–116% of reference	8–16% increase
Transient response time	100% reference	78–88% of reference	12–22% reduction
Overall operating efficiency	100% reference	104–110% of reference	4–10% improvement

The energy-consumption results further demonstrate the potential of intelligent powertrain management. Across the evaluated driving conditions, the AI-based strategy showed a consistent tendency toward lower battery energy demand. The improvement was not attributed to a single control action but resulted from coordinated management of motor torque, electrical power, and regenerative braking. During moderate-speed operation, the intelligent controller avoided unnecessary variations in motor command and maintained operation closer to efficient regions of the motor operating envelope. During acceleration, it adjusted the power demand according to the actual vehicle requirement rather than maintaining excessive torque for longer periods than necessary. This reduced unnecessary electrical losses and contributed to improved battery utilization. The difference became more noticeable under urban driving conditions, where frequent acceleration, deceleration, and idling events created repeated opportunities for inefficient power conversion. The AI controller also demonstrated improved behavior during transitions between operating modes. Instead of treating acceleration and braking as independent events, the intelligent strategy considered the preceding and current system states when determining the subsequent control response. Consequently, the battery experienced a more coordinated power-flow pattern, which contributed to reduced overall energy consumption.

The motor torque response provides another important indication of the effectiveness of the proposed approach. Under sudden accelerator commands, the conventional controller exhibited relatively larger deviations between the requested and delivered torque, followed by a settling period. The AI-based controller generated a smoother response while reaching the required torque more quickly. This improvement is significant because traction-motor torque directly influences acceleration quality and the driver's perception of vehicle responsiveness. Excessive torque overshoot can also increase electrical losses and impose unnecessary mechanical stress on drivetrain components. The AI controller reduced such undesirable behavior by considering several input variables instead of relying exclusively on instantaneous torque error. Its response remained comparatively stable when motor speed and battery conditions changed simultaneously. Under repeated acceleration and deceleration, the controller maintained its performance without producing substantial oscillations. This suggests that the trained model successfully learned the nonlinear relationship between operating conditions and appropriate control actions.

Table 2. Torque and Speed Response Characteristics

Driving Condition	Conventional Response	AI-Controlled Response	Discussion
Moderate acceleration	Noticeable tracking deviation	Closer tracking	Improved torque regulation
Rapid acceleration	Higher overshoot	Lower overshoot	Better transient adaptation
Constant-speed operation	Stable	More stable	Reduced control fluctuation
Sudden deceleration	Slower transition	Faster transition	Improved mode coordination

Repeated stop–start	Variable response	Consistent response	Greater adaptability

Regenerative braking results also showed a positive effect from the AI-based strategy. During deceleration, the intelligent controller evaluated braking demand together with vehicle speed and battery operating conditions to determine an appropriate level of regenerative torque. The conventional strategy recovered energy effectively under favorable conditions but was less flexible when battery state of charge or braking demand changed. The AI-based controller demonstrated improved coordination between mechanical braking and electrical regeneration. When the battery had sufficient capacity to accept additional energy, a greater proportion of the available braking energy was directed toward electrical recovery. When charging constraints became more restrictive, the controller reduced regenerative demand instead of attempting to force excessive charging power. This adaptive behavior helped maintain stable battery operation while improving energy recovery. The improvement in recovered energy is particularly important for urban driving because frequent deceleration events provide repeated opportunities to recover otherwise dissipated kinetic energy. The results therefore indicate that intelligent braking management can contribute to extending usable driving range without requiring an increase in battery capacity.
Battery behavior under the AI-based control strategy was also comparatively favorable. The intelligent controller maintained more balanced power demand and avoided prolonged operation at unnecessarily high current levels. Although the AI strategy was primarily developed for powertrain control, its consideration of battery state of charge and electrical operating conditions indirectly supported more effective battery utilization. The reduction in unnecessary high-power events can potentially reduce electrical stress and improve the consistency of battery operation. The effect was particularly evident during low-SOC operation, where the controller moderated power demand while attempting to satisfy the required vehicle performance. Instead of maintaining the same aggressive response regardless of available battery energy, the AI strategy adjusted its behavior according to the prevailing energy condition. This demonstrates the value of incorporating battery information into a powertrain controller rather than treating the motor and battery as independent systems.

Table 3. Energy and Battery-Related Results

Parameter	Conventional Control	AI-Based Control	General Observation
Battery energy consumption	Higher	Lower	Improved energy management
Peak battery current	Higher during transients	Comparatively reduced	Smoother power demand
SOC reduction per cycle	Greater	Lower	Better energy utilization
Regenerated energy	Moderate	Higher	Improved braking recovery
Power fluctuation	More pronounced	Reduced	More stable operation

The results obtained under variable road gradients further emphasize the adaptive capability of the proposed controller. When the vehicle encountered an uphill section, the power requirement increased because additional energy was needed to overcome gravitational resistance. The AI controller responded by modifying the motor operating command according to the changing load rather than maintaining a fixed response pattern. During downhill operation, the controller appropriately reduced propulsion demand and increased the opportunity for regenerative energy recovery. Similar adaptability was observed under changes in vehicle loading. Increased vehicle mass altered the acceleration requirement and road-load characteristics, yet the AI controller retained comparatively stable torque and speed tracking. This indicates that the learned control relationship was not restricted to a single nominal operating point. However, the results also show that AI performance depends strongly on the quality and diversity of the training data. When operating conditions moved substantially beyond those represented during training, small increases in tracking deviation were observed. This highlights the importance of exposing the learning model to sufficiently broad operating conditions during development.
The overall efficiency improvement can be attributed to the combined effect of improved torque regulation, reduced unnecessary electrical demand, better motor operating-point selection, and enhanced regenerative braking. Rather than producing a dramatic improvement in only one parameter, the AI-based controller generated moderate gains across several interconnected performance indicators. This is an important

observation because EV powertrain efficiency is determined by the interaction of multiple components. Improving motor efficiency alone may not produce significant system-level benefits if battery power management remains inefficient. Similarly, maximizing regenerative braking without considering battery limitations may negatively affect battery operation. The proposed AI strategy demonstrated the ability to coordinate these competing requirements within a unified control framework. The results therefore support the view that AI-based control is particularly useful when several powertrain variables must be considered simultaneously.

Despite these improvements, certain limitations were identified. AI model performance depends on appropriate training, representative datasets, and sufficient computational capability. The controller may also experience reduced prediction accuracy when exposed to operating conditions that differ substantially from its training environment. In addition, increased model complexity can create challenges for real-time implementation in embedded vehicle-control hardware. These considerations mean that AI-based control should be implemented together with conventional protection mechanisms, physical operating constraints, and appropriate fallback strategies. The results should therefore be interpreted as evidence of the potential of AI-based control rather than as an indication that conventional control methods are no longer necessary. Overall, the comparative findings demonstrate that AI-based powertrain control can improve energy utilization, dynamic response, regenerative braking performance, and operating adaptability. The combined improvements indicate that intelligent control offers a promising pathway toward more efficient and responsive electric vehicles, particularly when the controller is trained using diverse operating conditions and integrated carefully with established powertrain-control and safety mechanisms.

Conclusion

The study on **Performance Enhancement of Electric Vehicle Powertrain Systems Using AI-Based Control** demonstrates the potential of intelligent control techniques to improve the efficiency, responsiveness, and adaptability of modern electric vehicle powertrains. The comparative evaluation indicates that AI-based control can respond more effectively to variations in vehicle speed, torque demand, battery state of charge, road conditions, and regenerative braking requirements than conventional control approaches based on fixed operating parameters. Improvements were observed in torque and speed tracking, energy utilization, transient response, and regenerative energy recovery. By continuously processing information from the battery, motor, inverter, and vehicle operating environment, the intelligent controller can determine more appropriate control actions for changing driving conditions. The coordinated management of propulsion and braking power also contributes to reduced energy losses and improved utilization of available battery energy. These findings reinforce the importance of treating the EV powertrain as an integrated electromechanical system in which intelligent decision-making can influence overall vehicle performance rather than optimizing individual components in isolation.

The research further establishes that AI-based control offers a promising pathway toward more adaptive and energy-efficient electric mobility, although practical implementation requires careful attention to training-data quality, model robustness, computational requirements, and operational safety. An AI controller must remain reliable when exposed to conditions that may differ from those represented during model development, and therefore appropriate validation, physical constraints, monitoring mechanisms, and conventional safety-oriented control layers remain essential. Future investigations can extend the present work by incorporating real-world vehicle measurements, broader driving conditions, battery ageing characteristics, thermal effects, and hardware-in-the-loop or experimental validation. More advanced learning approaches can also be explored to support predictive energy management, intelligent fault detection, and personalized driving-condition adaptation. Overall, the findings suggest that combining artificial intelligence with established electric-drive control principles can provide a practical foundation for improving powertrain efficiency, driving performance, regenerative energy utilization, and system reliability. Such intelligent powertrain architectures can contribute significantly to the development of next-generation electric vehicles capable of achieving better energy utilization while maintaining responsive, stable, and reliable operation across diverse driving environments.

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