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Artificial Intelligence for Battery and Drive System Management in Electric Vehicles

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Abstract – Artificial intelligence (AI) is becoming increasingly relevant to the management of batteries and electric propulsion systems in electric vehicles (EVs), particularly for improving efficiency, operational safety, reliability, and driving performance. Conventional battery management systems (BMS) and drive controllers generally depend on mathematical models and predefined control strategies, whose performance can be affected by battery degradation, temperature variations, changing loads, and diverse driving patterns. AI-based approaches, including machine learning, deep learning, reinforcement learning, fuzzy systems, and digital-twin models, offer adaptive mechanisms for monitoring system conditions and making real-time control decisions. These techniques can estimate important battery parameters such as State of Charge (SOC), State of Health (SOH), Remaining Useful Life (RUL), and thermal condition, while supporting improved charging, discharging, and cell-balancing strategies. On the propulsion side, AI can assist torque regulation, energy-flow optimization, regenerative-braking control, and early identification of faults in motors, inverters, and sensors. The use of IoT communication, blockchain-supported BMS, and digital twins can further improve information security, data reliability, and condition-based maintenance. Nevertheless, practical implementation is constrained by data requirements, processing overhead, limited model transparency, and cybersecurity concerns. Combining AI with advanced battery systems and intelligent electric-drive control can therefore provide a strong foundation for developing safer, more efficient, dependable, and sustainable EV powertrains.

Key Words: **Artificial Intelligence (AI),Electric Vehicles (EVs),Battery Management System (BMS),State of Charge (SOC),State of Health (SOH),Machine Learning Deep, Learning Reinforcement, Learning Electric, Drive Systems Predictive ,Control Digital Twin Energy, Management Systems (EMS)**

1. INTRODUCTION

The increasing adoption of electric vehicles (EVs) requires reliable battery operation and coordinated powertrain control. An EV integrates the battery, power converter, traction motor, sensors, and supervisory controller, whose operation is influenced by ageing, temperature, load, speed, road gradient, and driving conditions [1], [2]. AI-based methods can learn relationships among electrical, thermal, and mechanical parameters and support SOC, SOH, SOP, and RUL estimation alongside conventional battery models [7]–[12]. Recent studies have also explored machine learning, deep learning, reinforcement learning, and digital-twin technologies for EV applications [13], [16], [28].

This paper examines AI-based coordination between the Battery Management System (BMS) and Electric Drive System (EDS). Joint consideration of battery condition, available power, traction demand, and driving conditions enables adaptive energy management, motor control, fault diagnosis, and degradation mitigation. The original material is consolidated into seven major sections while retaining the essential technical concepts, figures, tables, and references, providing a compact framework for integrated intelligent EV powertrain management

2. INTELLIGENT POWER ELECTRONICS AND ENERGY MANAGEMENT

A. AI-ENABLED POWER ELECTRONICS AND MOTOR CONTROL

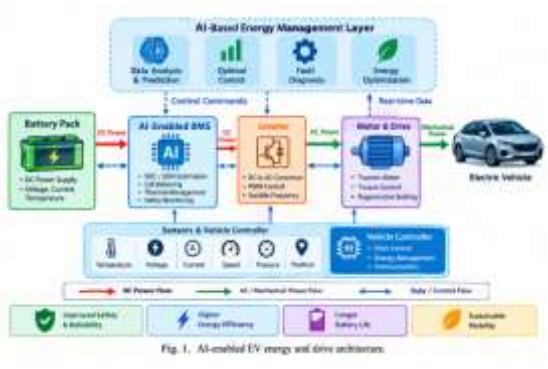


Fig1 AI-Enabled Electric Vehicle Architecture

Power electronic converters and traction-drive controllers determine how electrical energy stored in the EV battery is delivered to the propulsion motor. The inverter performs the

required electrical conversion and regulates the motor-side voltage and frequency, whereas the drive controller determines the appropriate torque and speed response based on instantaneous vehicle requirements [22]–[25]. In the architecture presented in Fig. 1, an intelligent supervisory layer combines measurements obtained from the battery, motor, sensors, and vehicle-control unit to enable adaptive coordination of the propulsion system. AI algorithms can process variables such as battery voltage, current, motor temperature, rotational speed, and instantaneous power demand to determine suitable converter and motor operating conditions [26]–[28].

AI-assisted predictive control can anticipate variations in traction demand and modify the motor operating point before significant changes occur. In addition, machine-learning-based diagnostic methods can analyse electrical and thermal signatures to detect developing abnormalities in traction motors, inverters, and sensing elements [29], [30]. Early identification of such operating anomalies can prevent severe component failures and reduce maintenance requirements. The combined use of intelligent control and predictive diagnostics can consequently enhance converter utilization, minimize avoidable power losses, improve propulsion efficiency, and increase the operational reliability of EV drive systems.

B. INTELLIGENT ENERGY MANAGEMENT AND BATTERY–DRIVE COORDINATION

Intelligent energy management enables coordinated operation of the battery, Battery Management System (BMS), inverter, traction motor, and vehicle controller to improve overall powertrain efficiency. The integrated architecture shown in Fig. 1 allows information from these subsystems to be processed collectively for adaptive power allocation. AI-based management strategies can evaluate battery state of charge (SOC), temperature, vehicle speed, road gradient, traffic conditions, and driver behaviour to estimate the required propulsion power [31]–[34]. During acceleration, the controller can regulate power demand according to battery capability and avoid unnecessary high-current operation. During regenerative braking, motor braking torque can be coordinated with the battery's allowable charging power to maximize energy recovery while maintaining safe operating limits. Furthermore, AI-based prediction of future power requirements can enable proactive adjustment of the powertrain operating point and reduce abrupt load variations [35], [36]. Such battery–drive coordination can improve energy efficiency, driving range, battery durability, and overall vehicle reliability [37].

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3. AI METHODS FOR BATTERY AND DRIVE APPLICATIONS

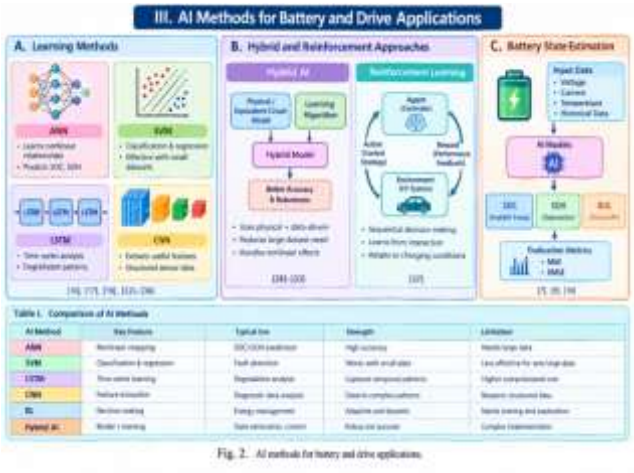


Fig.2 AI-Methods for battery and drive applications

A. LEARNING METHODS

AI-based learning methods offer effective computational approaches for predicting battery states and interpreting operating conditions within EV propulsion systems. Artificial Neural Networks (ANNs) are capable of learning complex nonlinear mappings between measured electrical and thermal variables and battery states such as SOC and SOH. Support Vector Machines (SVMs) provide reliable regression and classification capabilities and can be advantageous when the available training dataset is relatively small. Long Short-Term Memory (LSTM) architectures are particularly appropriate for time-dependent battery signals because they can retain information from previous operating conditions and capture degradation patterns. Convolutional Neural Networks (CNNs) can extract significant features from structured measurement and diagnostic data [16], [17], [19], [32]–[36]. The principal AI techniques and their representative EV applications are summarized in Fig. 2. Algorithm selection is governed by factors including estimation accuracy, training-data availability, processing requirements, and the specific operational objective of the EV system.

B. *HYBRID AND REINFORCEMENT APPROACHES.*

- Hybrid AI frameworks combine a physics-based or equivalent-circuit representation with a data-driven learning model. The model-based component describes the fundamental electrical behaviour of the battery, whereas the AI component learns nonlinear characteristics, uncertainties, and modelling discrepancies that are difficult to represent analytically [28]–[33].
- This combined architecture can enhance prediction robustness while reducing the requirement for extensive experimental datasets. Fig. 2 presents the conceptual arrangement of hybrid AI and reinforcement-learning techniques for EV applications.
- Reinforcement Learning (RL) formulates energy management as a sequential decision-making problem in which the controller learns

appropriate control actions from system feedback and performance rewards [37].

- These approaches are particularly useful for operating conditions that vary with battery state, power demand, traffic, and driving behaviour. Consequently, hybrid learning and RL techniques can enable adaptive battery supervision and dynamic energy-management decisions.

C. BATTERY STATE ESTIMATION

Accurate estimation of battery operating states is fundamental to safe and efficient EV control. SOC provides an indication of the remaining usable charge and directly affects propulsion capability, charging control, regenerative-braking operation, and range prediction. SOH reflects the progressive deterioration of the battery through parameters such as capacity loss and increasing internal resistance, whereas RUL provides an estimate of the remaining service period [7], [9], [16]. As depicted in Fig. 2, battery voltage, current, temperature, and historical operating information can be processed by AI models to determine SOC, SOH, and RUL. Model performance is commonly quantified using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Smaller estimation errors indicate improved state-prediction capability, enabling the BMS to select safer and more efficient operating conditions.

4. AI-ASSISTANT ELECTRIC-DRIVE CONTROL, BATTERY-DRIVE MANAGEMENT, AND ENERGY OPTIMIZATION IN EV'S

A. INTELLIGENT ELECTRIC-DRIVE CONTROL

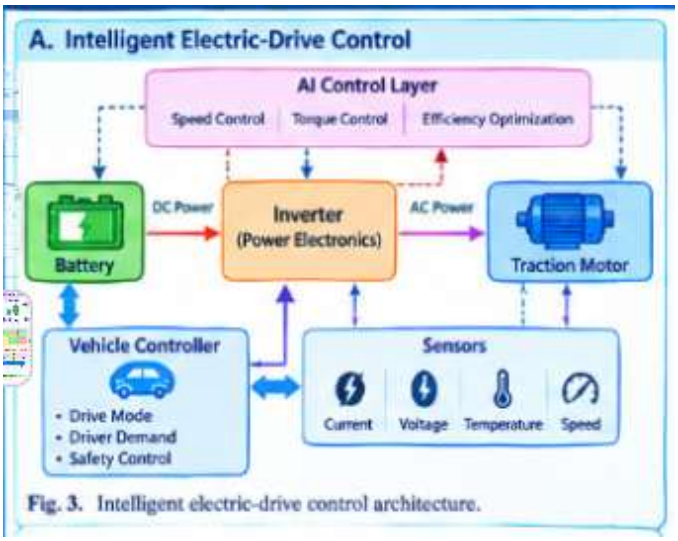


Fig. 3. *Intelligent electric-drive control architecture.*

The electric-drive system determines how efficiently electrical energy is converted into mechanical propulsion. It mainly consists of the battery interface, inverter, traction motor, sensors, and vehicle controller. **Fig. 3** illustrates an AI-assisted electric-drive architecture in which operating information is continuously supplied to the control layer. Parameters such as motor speed, torque demand, battery voltage, current, and temperature can be analysed to select suitable control actions [22]–[26]. AI-based predictive techniques can estimate upcoming torque requirements and modify motor commands before major changes occur. This can reduce unnecessary switching losses and improve the dynamic response of the drive. AI can also assist in identifying abnormal motor, inverter, and sensor behaviour at an early stage [27]–[30]. During regenerative braking, intelligent control can coordinate motor braking torque with the permissible battery charging power. The controller can therefore recover available braking energy without imposing excessive electrical stress on the battery. **Table** compares conventional and AI-assisted drive control. Overall, intelligent electric-drive control can improve efficiency, reliability, response, and energy utilization in EV operation.

B. INTEGRATED BATTERY–DRIVE MANAGEMENT

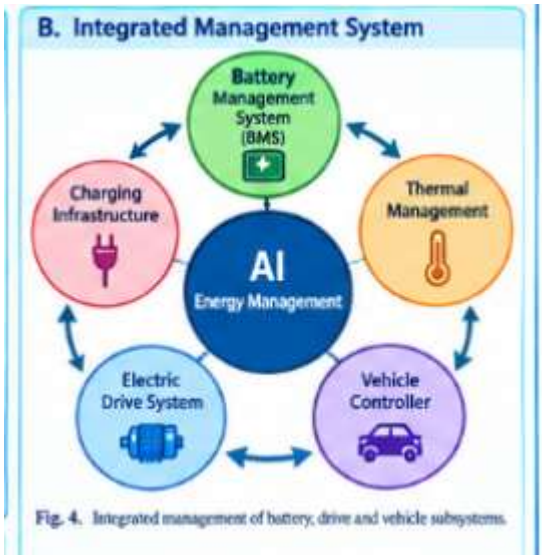


Fig.4. Integrated management of battery, drive, and vehicle subsystems.

Integrated management coordinates the battery, BMS, inverter, motor, thermal system, and vehicle controller rather than treating each subsystem independently. **Fig. 4** presents this coordinated arrangement, where AI processes information obtained from multiple vehicle subsystems. Battery SOC, SOH, temperature, vehicle speed, torque demand, road conditions, and driver behaviour can be considered together during energy-management decisions [31]–[34]. During acceleration, the available battery power can be matched with motor demand to avoid unnecessary energy consumption. During regenerative braking, the system can determine whether the battery can safely accept the recovered energy. AI-based prediction of future power demand can further improve energy allocation and reduce battery stress [35], [36]. Thermal information can also be included to prevent excessive battery and motor temperatures. **Table V** summarizes important functions of an integrated battery–drive system. Such coordination improves communication between subsystems and can contribute to greater driving range, better efficiency, longer battery life, and improved vehicle reliability [37]. Therefore, integrated AI management provides a broader framework for intelligent EV operation.

C. TABLES

TABLE 1:

Comparison of Conventional and AI-Assisted Drive Control

Parameter	Conventional Control	AI-Assisted Control
Control basis	Fixed/control equations	Data-driven and adaptive
Response	Predetermined	Adaptive
Fault detection	Usually separate	Can be integrated
Energy optimization	Limited	Higher potential
Changing conditions	Less flexible	Better adaptability

TABLE 2: *Functions of Integrated Battery–Drive Management*

Function	Main Input	Expected Benefit
Power coordination	SOC, torque demand	Efficient energy use
Thermal control	Temperature	Improved safety
Regenerative braking	Speed, SOC	Energy recovery
Fault monitoring	Sensor data	Early diagnosis
Demand prediction	Driving conditions	Reduced battery stress

5. PERFORMANCE, FAULT DIAGNOSIS, AND COMPARATIVE EVALUATION.

A. PERFORMANCE EVALUATION

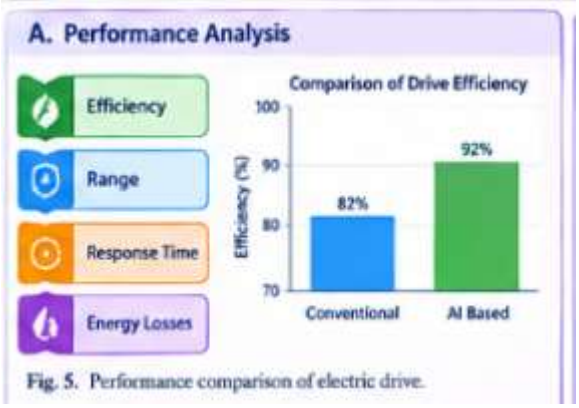


Fig. 5. AI-assisted EV performance evaluation.

Performance evaluation determines whether an AI-based EV system provides practical improvement over conventional approaches. Important measures include energy efficiency, driving range, response time, power loss, estimation error, and computational requirement [22]–[26]. **Fig. 5** represents the major performance indicators considered during evaluation. Battery models can be assessed through SOC and SOH prediction errors, whereas electric-drive performance can be examined through torque response, efficiency, and energy consumption. A reliable evaluation should consider both prediction accuracy and real-time execution capability [27]–[31].

B. AI-BASED FAULT DIAGNOSIS

Fault diagnosis is essential for improving the safety and reliability of electric vehicles. AI techniques can analyse parameters such as voltage, current, temperature, vibration, and other sensor measurements to detect abnormal operating conditions in batteries, motors, inverters, and related components [32]–[36]. Classification algorithms can separate normal operating states from different fault conditions, while predictive models can identify early signs of component degradation. Detecting faults at an early stage can help prevent serious failures, reduce maintenance requirements, and improve component service life. AI-based diagnostic systems can therefore support faster fault identification and more reliable vehicle operation [37].

C. COMPARATIVE EVALUATION OF AI METHODS

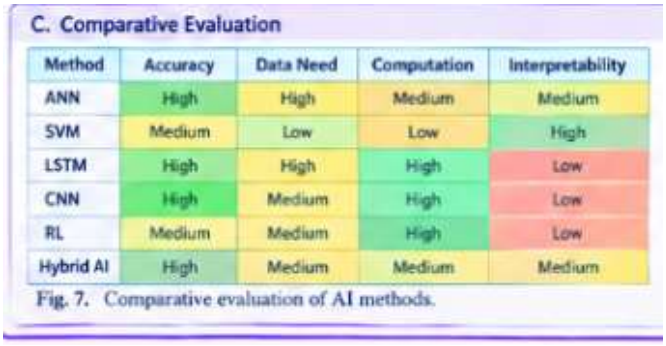


Fig. 7. Comparative evaluation of AI methods.

Different AI techniques offer different levels of accuracy, computational demand, data requirement, and interpretability. **Fig. 7** provides a conceptual comparison of commonly applied methods. ANN and LSTM are useful for nonlinear prediction and sequential data, whereas SVM performs well with comparatively smaller datasets [16], [19]. CNN is suitable for structured diagnostic information, while RL supports adaptive decision-making [34]–[37]. Hybrid AI combines physical knowledge with learning and can improve robustness [28]–[33]. Hence, the most suitable method depends on the specific EV application.

D. RELIABILITY AND REAL-TIME OPERATION

An AI model for EV control must provide accurate results within the required operating time. Accuracy alone is insufficient when a model requires excessive processing resources or produces delayed decisions. Processor capability, sampling frequency, model complexity, communication delay, and fault tolerance should therefore be considered [16], [19], [34]–[37]. **Table VI** compares important evaluation factors for AI-based EV systems. Testing under different temperatures, loads, speeds, and driving conditions can reveal limitations that may not appear in laboratory datasets. A combined evaluation provides a more realistic measure of system performance.

Evaluation Factor	**Purpose**	**Desired Characteristic**
Accuracy	Prediction quality	Low error
Response time	Real-time control	Fast
Data requirement	Training feasibility	Moderate/low
Computation	Hardware suitability	Efficient
Interpretability	Decision understanding	High
Robustness	Changing conditions	Stable

6. CHALLENGES AND FUTURE DIRECTIONS

A. LIMITED DATA AND MODEL INTERPRETABILITY

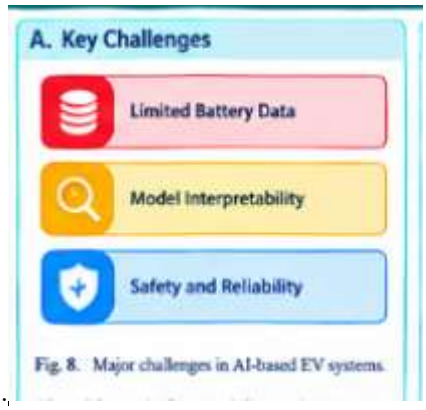


Fig. 8. Major challenges in AI-based EV systems.

AI performance depends strongly on the availability and quality of training data. Battery ageing, temperature changes, driving behaviour, charging patterns, and road conditions produce highly variable datasets. Insufficient data can reduce model generalization when the vehicle encounters unfamiliar operating conditions [16], [19], [34]–[36]. **Fig. 8** highlights limited data and model interpretability as major challenges. Complex AI models may also provide accurate predictions without clearly explaining their decisions. This can reduce confidence in safety-critical EV applications. Explainable AI can improve transparency by providing understandable information about model decisions and important input parameters.

B. ADVANCED AI AND DISTRIBUTED LEARNING

Future EV systems can benefit from explainable AI, federated learning, edge computing, and improved battery models. **Fig. 9** illustrates these potential development directions. Explainable AI can improve understanding of model outputs, while federated learning can enable learning from distributed vehicle data without requiring all raw information to be transferred to a central location [28], [32], [35]–[37]. Edge computing can reduce communication delays by processing selected tasks close to the vehicle. Improved electrochemical and hybrid models can also strengthen battery-state prediction. Combining these technologies may improve accuracy, privacy, computational efficiency, and real-time performance.

C. INTEGRATED AI FRAMEWORKS

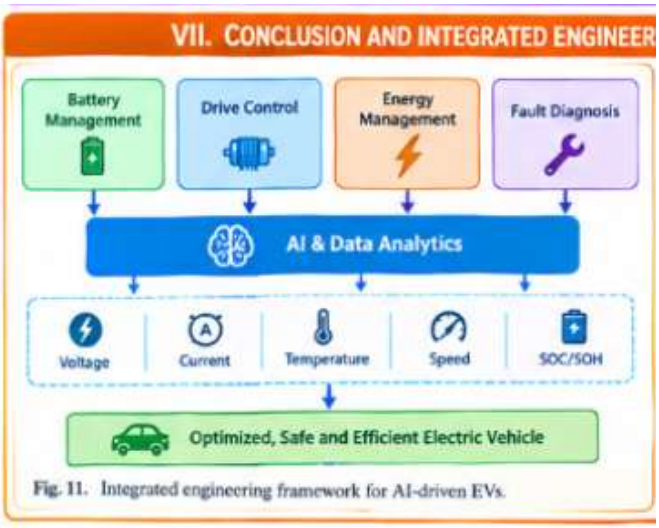


Fig. 11. Integrated engineering framework for AI-driven EVs.

Future research should move toward unified AI frameworks that consider battery condition, electric-drive behaviour, thermal effects, and vehicle-level energy management together. Many existing approaches focus on individual subsystems, which can restrict coordinated decision-making [31]–[37]. **Fig. 11** represents an integrated framework in which information from several EV subsystems is processed through a common AI layer. Research should emphasize standardized datasets, common evaluation procedures, hardware implementation, and real-world validation. Such development can improve energy efficiency, battery durability, fault detection, and vehicle reliability. Integrated frameworks can also provide a stronger foundation for safe and adaptive EV control under changing operating conditions.

7. CONCLUSIONS

Artificial Intelligence provides a promising approach for improving battery management, electric-drive control, energy optimization, and fault diagnosis in electric vehicles. Learning methods such as ANN, SVM, LSTM, and CNN can extract useful relationships from battery and vehicle data, while reinforcement learning and hybrid approaches can support adaptive control [7], [16], [19], [28]–[37]. Accurate estimation of SOC, SOH, and RUL helps the BMS make appropriate decisions during charging, acceleration, and regenerative braking. Intelligent electric-drive control can simultaneously improve torque regulation and energy utilization. **Fig. 11** summarizes an integrated engineering framework in which battery management, drive control, energy management, and fault diagnosis communicate through an AI-based decision layer. This arrangement enables information from voltage, current, temperature, speed, and battery-state measurements to be considered jointly. However, limited datasets, computational requirements, interpretability, and real-world validation remain significant challenges [16], [19], [34]–[37]. Future research should emphasize explainable AI, federated learning, edge computing, standardized datasets, and integrated battery–drive models. Overall, coordinated AI management can support safer, more efficient, reliable, and sustainable electric mobility while improving the practical utilization of battery and drive-system information

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