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Iot and AI Framework for Real-Time Control of Electrical Vehicles

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ABSTRACT

Utilizing the Industrial Internet of Things in electric vehicles represents a major shift toward transportation systems that are more sophisticated, interconnected, and efficient. This research provides a thorough examination of the importance of the Industrial Internet of Things in improving multiple facets of electric vehicle technology, such as predictive maintenance, vehicle connectivity, personalized user management, energy and fleet optimization, and autonomous features. Alongside case studies showcasing practical implementations, important IoT applications are analyzed, including advanced driver-assistance systems and vehicle-to-grid connections. The findings show that although grid stabilization lowers electricity consumption and improves functional sustainability, it is the advanced charging stations enabled by IoT that shorten charging durations. Battery Management Systems (BMSs) assist in minimizing maintenance frequency and extending battery life. The combination of the Internet of Things (IoT) and artificial intelligence (AI) improves the safety and effectiveness of autonomous EV operations through the optimization of driving behavior, route planning, and energy consumption. This report addresses a number of challenges, including cybersecurity, connectivity, and integration with antiquated systems. It also discusses new trends driven by AI, machine learning, and developing IoT technologies. By analyzing the overlap between IoT and EVs, this study highlights how IoT may accelerate the global transition to smart and environmentally friendly transportation solutions.The rapid adoption of electrical vehicles (EVs) demands intelligent frameworks capable of ensuring efficiency, safety, and sustainability in real-world environments. This study proposes an integrated IoT and AI-based framework for the real-time control and monitoring of EVs. The IoT layer enables seamless data acquisition from onboard sensors, charging infrastructure, and traffic systems, while cloud and edge computing platforms ensure continuous communication and interoperability. Artificial Intelligence algorithms are employed for predictive analytics, including energy consumption forecasting, battery health estimation, adaptive route optimization, and driver behavior analysis. Furthermore, the framework supports Vehicle-to-Grid (V2G) communication, facilitating smart energy distribution in renewable-integrated grids. Experimental simulations and prototype implementation highlight improvements in battery utilization, reduction in charging delays, and enhanced driving safety. The proposed IoT–AI framework demonstrates its potential as a robust solution for advancing next-generation smart mobility and sustainable transportation ecosystems.

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1. INTRODUCTION

The development of the electric vehicle (EV) sector marks a paradigm shift in addressing global issues like urban traffic, global warming, and sustainable energy solutions. As nations strive to meet reduced pollution targets, the adoption of EVs has been significantly accelerated. To address issues with battery performance, EV charging configuration, car maintenance, and customer experience, smarter, more efficient, and highly networked EV ecosystems are required. In order to improve efficiency and inspire new ideas, the Internet of Things seems to be a revolutionary digital architecture that makes it easy to integrate online platforms with industrial procedures [1]. This article explores the confluence of EV and IoT technologies, providing a comprehensive analysis of the main applications, advantages, and difficulties. An overview of IoT's evolution, including achievements related to its structural components and standardization needs, opens this conversation. Next, using real-world case studies, we examine the role of IoT in a variety of EV applications, including as automated driving, predictive maintenance, and V2G integration. This analysis concludes by highlighting future trends that will reimagine the potential of IoT application in the EV industry, such as the convergence of AI and ML. The goal of this research is to comprehend how the Internet of Things might influence the development of the upcoming generation of intelligent and environmentally friendly transportation systems.

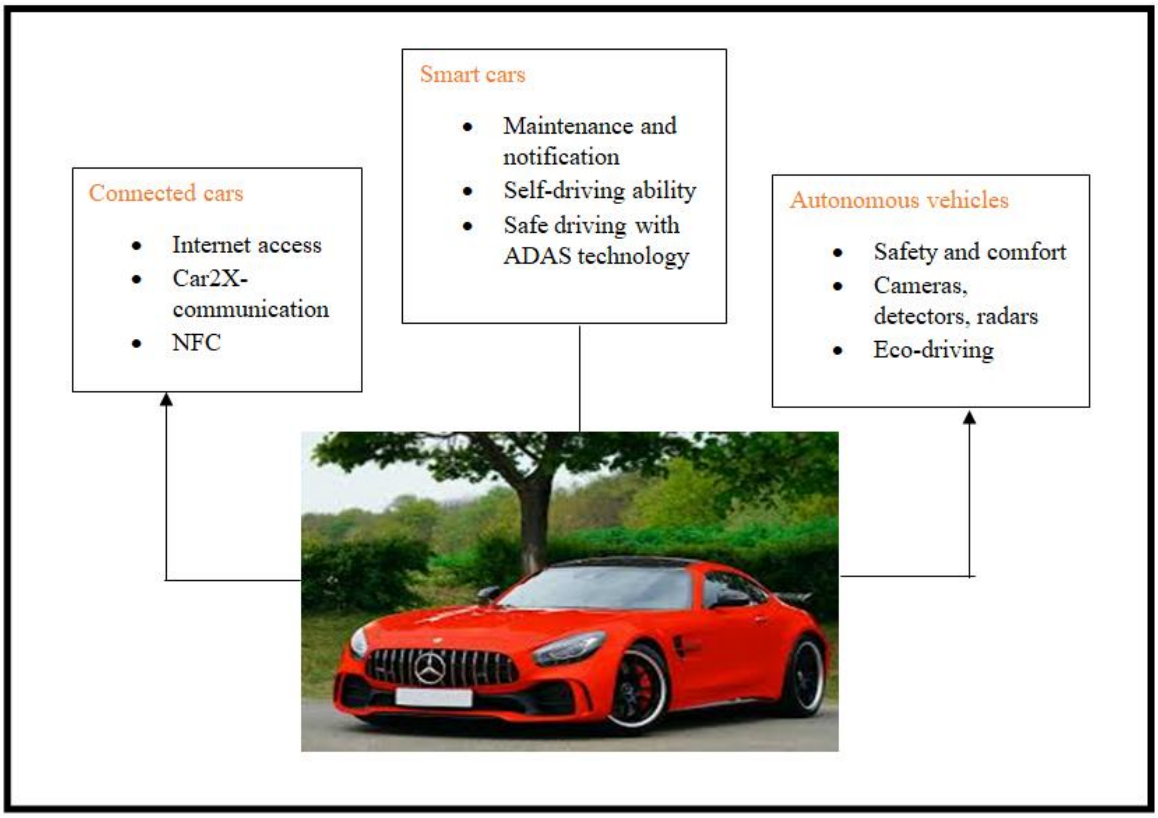


Fig. 1. IOT in EV Technologies

The demand for environmentally friendly transportation options is causing a radical change in the automobile sector toward electric vehicles, or EVs. This study examines how to integrate Internet of Things (IoT) and artificial intelligence (AI) technologies in order to enhance the performance, efficiency, and user experience of electric vehicles. Through a comprehensive review of existing literature and case studies, this research elucidates the contributions of AI and IoT to various aspects of electric vehicle technology, including battery management, predictive maintenance, autonomous driving, and smart charging systems. Transportation systems are changing due to the integration of artificial intelligence (AI) and the Internet of Things (IoT) into electric vehicles (EVs) [2]. This study examines the complex interactions between IoT and AI in the context of the EV ecosystem, examining how they might work together to transform sustainability, safety, and efficiency. This paper explores how IoT sensors allow real-time data collection from EVs and infrastructure, enabling AI-driven analytics for optimizing energy consumption, forecasting maintenance needs, and improving user experience advancements. Additionally, it talks about the benefits and difficulties that come with the electric car ecosystem's broad adoption of IOT and AI solutions. This study offers insights into the possibilities and possible effects of IOT and AI in electrifying the road by examining existing trends and developments.

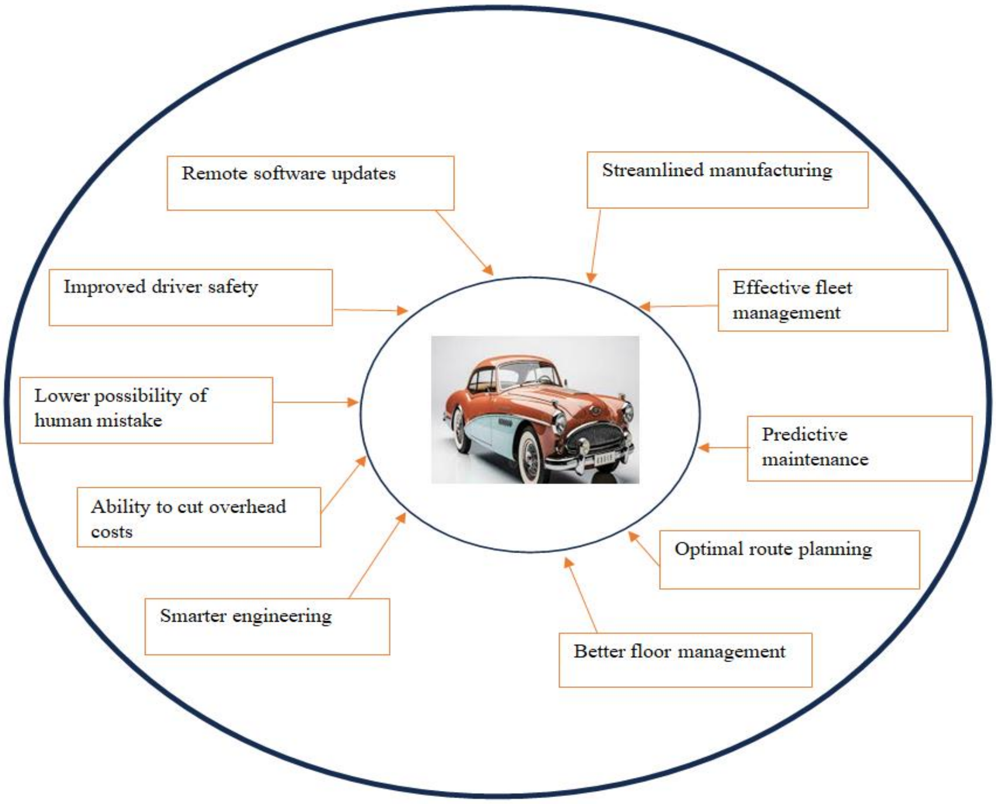


Fig. 2. challenges for EVs.

Rooted in the broader concept of the Internet of Things, the Industrial Internet of Things amplifies its possibilities for extensive industrial systems. Within the realm of electric vehicles, the Internet of Things facilitates adaptive regulation, predictive analysis, and real-time tracking of vehicle systems, thereby ensuring optimal performance in a variety of applications. IoT technologies—whether they be Advanced Driver-Assistance Systems (ADASs), fleet energy management, or Vehicle-to-Grid (V2G)—are essential to transforming EVs into intelligent, self-driving, and adaptable gadgets. Thanks to vehicle-to-grid technology, EVs can communicate directly with the power grid, allowing them to store excess energy and return it when needed. Artificial intelligence significantly enhances energy storage systems (ESSs) and boosts the accuracy and efficiency of power systems, which are vital for integrating renewable energy sources. On the other hand, an ADAS refers to a system that aims to improve comfort while driving and increase safety [3]. Furthermore, the IoT facilitates the aggregation of evaluations from extensive datasets, thereby enabling participants to make analytical choices that enhance the safety, sustainability, and optimization of EV operations. For IoT applications in EVs, optimizing techniques like hybrid metaheuristic algorithms are crucial for handling the complexity of interconnected systems. They guarantee quicker decisions and effective resource allocation in real-time settings. Other disciplines, such photovoltaic systems, have also been investigated using similar optimization frameworks. Financial incentives have encouraged residential customers to put solar PV systems on their roofs. The majority of solar PV systems export their excess electricity to the utility grid and are connected to it. Customers have begun to use EVs for their everyday commutes. For grid-connected solar PV systems and electric vehicles to be used effectively, they require an energy management system. The literature has documented residential energy management frameworks with various aim functions. In order to increase profits, the majority of the stated purpose functions encourage customers to export their domestically produced electricity to the utility grid. As discussed in the last section, there are serious technical problems that arise when more electricity is exported into the low voltage, weak distribution system. Therefore, in order to reduce the technical problems associated with the integration of solar PV systems and EVs at the low voltage distribution feeder, an energy management framework with a novel target function is required. In this study, the R-PHEV application is the main focus [4]. The objectives of the proposed models are

- Utilize IoT sensors and infrastructure to collect real-time data from EVs, charging infrastructure, and traffic systems.

- Develop AI-powered charging scheduling algorithms to minimize charging delays and optimize battery utilization.
- Implement real-time fault detection and predictive maintenance to enhance driving safety and reduce the risk of accidents.
- Support V2G communication to facilitate smart energy distribution in renewable-integrated grids.
- Contribute to the development of next-generation smart mobility and sustainable transportation ecosystems.

The remainder of the questionnaire is structured in this manner. Section 2 lists the main block chain methods that have been used to cloud based storage analysis and are covered in the survey. Section 3 describes proposed model. Section 4 examines the results and unresolved issues in a number of use cases. Lastly, section 5 concludes the paper

2. REVIEW OF LITERATURE

Human, social, economic, and environmental characteristics are the four different elements that can support environmental sustainability (Omahne et al., 2021). It is possible to support the welfare of present and future generations by combining these four essential elements. In the meantime, modern life, which struggles with environmental justice, requires transportation. In particular, transportation contributes to the global rise in carbon emissions (Petrauskienė et al., 2021). Human-caused climate change is a factor in dangerous acid rain, urban air contamination, ocean and coastal acidification, and the melting of glaciers and polar ice. As a result, environmental suitability is jeopardized.

Cloud platforms are becoming more accessible, enabling both businesses and consumers to acquire the necessary infrastructure for scaling up without the need to handle all aspects of management on their own [Meniem, M.H.A., et al, 2012] [5]. As machine learning and analytics advance, and as access to large amounts of cloud-stored data improves, communication could become more efficient. Advancements in neural networks make natural language processing (NLP) on IoT devices possible and cost-effective.

Although electric vehicles are becoming more and more popular as greener substitutes for gasoline-powered vehicles, there are still environmental issues with them. The total environmental impact of EVs is largely determined by their technologies, especially fuel cell and battery technology. Therefore, evaluating the environmental effects of EVs with an emphasis on resource sustainability and greenhouse gas (GHG) emissions may prove to be a significant problem. These difficulties include the manufacturing of fuel cells and batteries. Energy-intensive procedures are used in the manufacture of batteries, particularly lithium-ion batteries. GHG emissions arise from the extraction and processing of raw materials such as nickel, cobalt, and lithium (Xiong et al., 2020; Franzò and Nasca, 2021). Since fuel cells offer a higher energy density than batteries, they have demonstrated encouraging first results when compared to other energy storage medium (Muthukumar et al., 2021). However, producing hydrogen for fuel cells might result in greenhouse gas emissions, especially if it comes from fossil fuels (gray hydrogen). To reduce these emissions, however, green hydrogen—which is created with renewable energy through electrolysis and other processes—is becoming more popular [6]. In order to boost the efficiency of battery and fuel cell technologies and reduce reliance on rare and environmentally damaging materials, focused research employing intelligent technologies is necessary (Abdelkareem et al., 2021).

The potential for connected and automated vehicles (CAVs) to focus on sustainability, mobility, and safety concerns has been examined. Examined is the most recent trend toward artificial intelligence and the Internet of Things (IoT), which can help with the investigation of autonomous vehicles. [To et al., C.N. 2018]. A study has been conducted to provide insight into the potential challenges and future prospects related to autonomous vehicle (AV) technologies. An analysis of the development of the Internet of Things (IoT) in relation to its use in the automotive sector has been conducted to shed light on different areas, including connected car services and applications, vehicle communications, IoT in intelligent transportation, IoT-based supply chain management in the automotive industry, and next-generation vehicles. Documentation reflects considerable advancement in these areas. As per Guerrero-Ibanez et al. in 2018, it is crucial to connect electric vehicles with Internet of Things-based technologies to monitor their battery life.

The transportation sector is still focused on reaching NetZero emission status because of the environmental issues surrounding EVs. According to Dönmezçelik et al. (2023), nations are rapidly creating and putting into effect long-term emission reduction programs. When assessing the transportation sector's feasibility in achieving the Net Zero Emission 2050 targets, it is essential to consider various variables, challenges, and possible solutions (Khan et al., 2023). Even though it is a complex process, the industry can significantly reduce emissions due to regulatory measures, technological breakthroughs, and changing customer attitudes. Government policies and regulations are crucial not only for linking each phase of the electric vehicle process—from the development to the application of innovative technologies—but also for guiding the transport industry in the direction of net-zero emissions [7]. Incentives, legislation that promotes environmentally friendly technologies, and emissions regulations can all ignite transformations in the sector.

A robust network of hybrid charging stations and infrastructure is essential for the widespread adoption of electric vehicles, ranging from AC home charging to DC extreme fast charging (Pagani et al., 2019). In order to provide an effective way to lower running expenses, save fuel, and assist the environment, this article has been structured to look at the entire spectrum of charging systems. The growing industrialization of electric vehicles (EVs) allows us to attain the essential indications when various transmitter and receiver devices are paired, thanks to the interoperability of wireless charging systems. Charging vehicles with V2G (vehicle-to-grid) technology will help to balance the electrification of transport by facilitating a two-way energy exchange between electric vehicles and the grid (Das et al., 2020).

Recent developments include the use of blockchain technology and distributed control for effective energy distribution and dynamic load balancing. For instance, bidirectional power flow made possible by V2G and G2V technology balances grid demand and reduces energy expenses. Furthermore, utilizing renewable energy sources such as solar-powered charging stations enhances sustainability. These measures promote renewable energy use, decrease peak demand, and guarantee grid reliability (Hu et al., 2022; Hu and Li, 2021; Ma et al., 2024).

Some of the challenges that contribute to the inherent complexity of internal energy management in EVs include: the dynamic nature of driving conditions; the fluctuating power demands of various vehicle subsystems; the need to balance energy from different sources; and the need to balance energy distribution in order to maintain high efficiency while extending battery lifespan. To ensure optimal functioning and longevity of the battery, an EV's EMS needs to effectively manage the power transfer among the battery, engine, and auxiliary parts, adjusting as necessary in real time. It is vital to achieve high energy efficiency in circumstances where driving behavior, acceleration, and regenerative braking vary frequently, as this complicates the establishment of such a balance. In-wheel motor technology in a next-generation electric car improves regenerative braking and removes mechanical middlemen, increasing system efficiency [8]. While managing critical constraints such as battery health and safety (Tie and Tan, 2013, Tie and Tan, 2012, Salari et al., 2023, Mastoi et al., 2022), the two-stage predictive controller improves vehicle mileage by over 24%.

Often referred to as "dumb charging," uncontrolled energy management techniques prioritize user comfort over system effectiveness. Plug-and-charge technology enables instantaneous charging without controlling power flow according to grid circumstances or vehicle demand. This approach controls the charging process's timing by depending on time-of-use (TOU), which could cause the distribution system to overflow. In addition to exceeding network capacity, high penetration levels for uncontrolled EV charging may result in load imbalance and possible problems with power quality. Notwithstanding these disadvantages, EV customers continue to favor unregulated charging because of its ease of use and adaptability (Upadhyaya and Mahanta, 2023, Katkar and Goswami, 2020).

An effective EMS ensures that energy consumption is balanced across the vehicle's powertrain, auxiliary systems, and energy storage units. The EMS must meet a complicated optimization challenge, as it needs to allocate power dynamically in real time according to driving patterns and demand. This necessitates advanced control methods. Suhail et al. (2021) state that uncontrolled energy management, particularly instantaneous and unregulated charging and discharging, results in inefficient energy use, battery degradation, and a diminished driving range.

Chen et al. (2023) proposed a fast-charging station energy management strategy founded on deep reinforcement learning. A mathematical optimization model is developed to handle peak power limitations and lower the costs of daily electricity purchases. The deep deterministic policy gradient algorithm is used to construct the control strategy. To confirm that the suggested control technique is effective, a case study is conducted. The results show a notable drop in peak load power, confirming the efficacy of the approach [9]. The deep reinforcement learning approach's scalability and computational complexity for large-scale fast-charging networks are yet unresolved.

As semiconductor technology advanced, power-efficient and reasonably priced processors were introduced, enabling the integration of billions of devices. A revival and a whole change were brought about by the introduction of RFID (Radio-frequency identification) tags, low-power semiconductors with wireless communication capabilities, and the expansion of broadband internet, cellular, and wireless networking. An essential step for the IoT to scale is the adoption of IPv6, which among other things gives each device an adequate number of IP addresses [H.Khayyamm et al. 2020].

The Internet of Things (IoT), which utilizes objects that can be linked to the internet via embedded devices and facilitate seamless communication among people, processes, and things, has emerged in recent years as one of the most important technologies of the twenty-first century. Access to inexpensive and low-power sensor technology is made possible by the Internet of Things, which also enables connection that allows a variety of network protocols for effective data transfer. [IK. Selvaraja and colleagues, 2008].

Detailed vehicle data in EV-EMS can be leveraged by advanced machine learning models through various approaches customized to the variable and multifaceted operating conditions of EVs. Fuzzy logic and adaptive neuro-fuzzy inference systems (ANFIS) controllers offer interpretable and effective management of battery performance in stable and predictable systems. However, in complex situations characterized by highly variable or uncertain conditions—such as rapid shifts in driving behavior, inconsistent battery usage, or severe environmental factors—their effectiveness can be constrained because they depend on static models and pre-established rule sets. However, despite their processing demands, DRL and deep learning approaches can optimize energy usage, extend longevity, and improve efficiency by leveraging large volumes of data [10]. The performance of hybrid energy storage systems is further improved by concurrent learning-based techniques, which lower energy loss and increase disturbance resilience. For EVs to be widely adopted, charging systems must be both practical and efficient. To meet consumer needs, a variety of techniques have been developed, from quick convenience charging to long-term energy sustainability.

3. METHODOLOGY

Using AI, algorithms assess real-time information from IoT sensors located in electric vehicles and their environment. These adaptive control algorithms aim to address problems such as range anxiety, the optimization of charging infrastructure, and energy efficiency. This study primarily focuses on decision-making related to energy allocation within vehicles, ensuring that AI-driven solutions optimize power distribution at the vehicle level, even when certain EMS techniques (such as V2G, G2V, and V2H) connect to external power sources. To address these challenges, there is an increasing use of AI methods, which can help develop improved energy management strategies tailored to the changing nature of EV operation. With the integration of predictive analytics, machine learning, and neural networks, AI is able to dynamically adjust energy consumption based on a variety of driving conditions, user preferences, and environmental factors like temperature or terrain.

AI has surfaced as a disruptive influence in EV technology, especially concerning the development and operation of system control and battery management systems. To address the shortcomings of conventional models, researchers and engineers are creating BMS solutions that leverage AI techniques like ML, DL, and RL for greater precision, flexibility, and effectiveness. Temperature, voltage, and current are important input parameters that are used to assess battery safety and performance [11]. Power management, as well as estimating SOC and SOH, monitoring battery cell performance, and predicting remaining useful life (RUL), are all essential functions. Reliability and efficiency are improved through advanced thermal management, fault diagnostics, discharge control, secure data collection, and cell balancing. For smooth data flow, the architecture also incorporates networking and communication systems. The framework's core components are AI and control systems, which use real-time data for optimization, decision-making, and predictive analytics. This all-encompassing strategy guarantees intelligent, safe, and effective BEM for EVs.

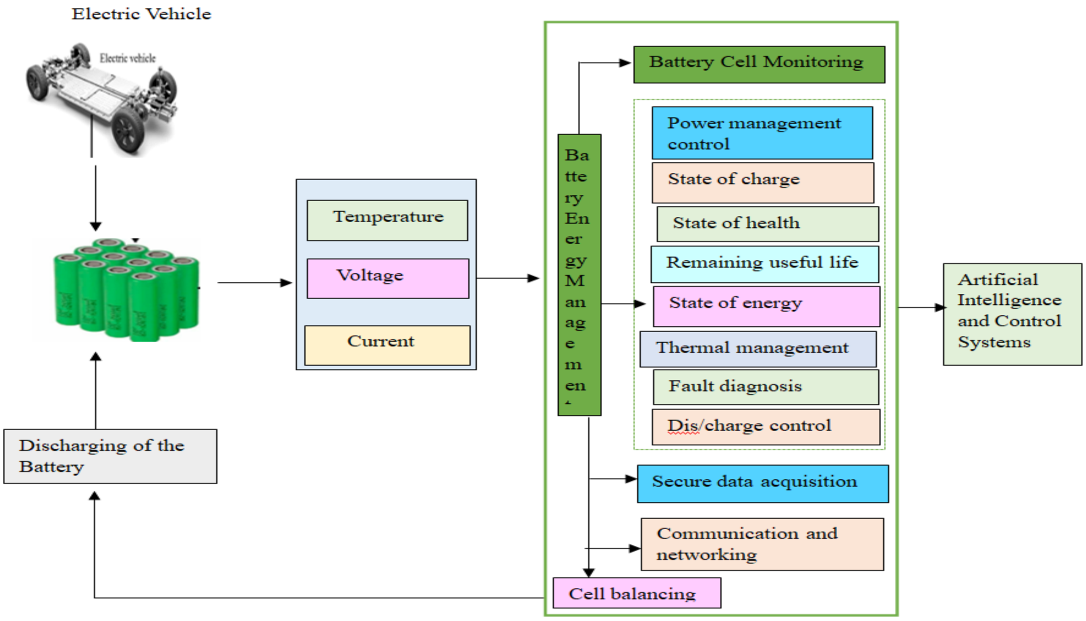


Fig. 3. Framework for BEM and control in EVs

AI-driven advancements offer predictive and real-time capabilities that are essential for controlling the complex dynamics of EV batteries. By considering temperature variations, load changes, and battery aging, machine learning algorithms trained on historical and real-time data can provide more accurate estimates of SOC and SOH than traditional methods. Neural networks (NNs), in particular, have demonstrated potential for simulating complex, non-linear interactions within battery systems, which facilitates more precise problem identification and temperature management. RL allows for the dynamic optimization of power allocation, energy distribution, and regenerative braking strategies across different driving conditions by equipping BMSs and system controls with self-learning capabilities [12]. Even in the face of unpredictable operating conditions, this flexible method can greatly improve energy efficiency and prolong battery life.

The incorporation of IoT and big data analytics enhances AI's capabilities in EV systems. Vehicles outfitted with IoT technology produce significant volumes of operational data. This information can be employed to improve the training of AI models. As a result, predictive maintenance and optimization at the fleet level are enabled. Predictive algorithms, for example, can anticipate battery degradation or malfunctions, lowering maintenance costs and improving safety. AI makes it possible for numerous EVs to have dynamic energy management at the fleet level, opening up new possibilities for applications in public and commercial transportation. The figure's depiction of the worldwide emissions trend highlights how urgently transportation systems need to undergo radical reform. Developments in AI-driven BMSs and system controls are essential as EV use increases on a global scale, not just for enhancing the reliability and effectiveness of single vehicles but also for addressing larger environmental challenges. The integration of AI, IoT, and big data will enable improvements in EV performance, ease the shift to a low-carbon economy, and create a sustainable future with connected mobility. Effective methods for optimizing energy management in electric vehicles (EVs) using more accurate data from the vehicle are provided by machine learning models such as fuzzy logic, ANFIS, deep reinforcement learning, and deep learning. These methods will guarantee peak performance by dynamically adjusting to changes and enhancing battery performance and longevity [13]. The suggested taxonomy guarantees that energy consumption, charging methods, and battery management are clearly differentiated from each other by reducing conceptual similarities. While charging solutions prioritize scheduling, grid interface, and infrastructure usage, energy consumption focuses on AI-driven optimization of driving efficiency and power distribution. Regardless of the energy efficiency or charging logistics of the vehicle, battery management focuses on preserving the battery's longevity and health. This organized framework enhances clarity by enabling detailed analysis of AI-driven solutions across each domain. Even though deep learning and DRL require a lot of processing, they will surpass the fuzzy logic model in terms of learning capabilities when used on a stable system.

To meet these demands and guarantee real-time performance, sophisticated hardware accelerations and algorithmic optimizations are required. The main hardware accelerators used to efficiently perform the simultaneous calculations needed for deep learning models are Graphics Processing Units (GPUs) and Tensor Processing Units (TPUs). Moreover, Application-Specific Integrated Circuits (ASICs) and Field Programmable Gate Arrays (FPGAs) provide tailored acceleration with reduced power usage, rendering them appropriate for embedded EV applications. Additionally, several methods for model compression—including quantization, pruning, and knowledge distillation—can greatly diminish computing overhead by reducing model size and inference latency [14]. Hybrid systems that combine rule-based control with AI-driven adaptations improve the feasibility of real-time operations. These methods utilize field expertise to make complicated decision-making processes easier. AI-driven EV energy management systems (EV EMS) can optimize energy management techniques in real time and more efficiently by integrating these hardware and software advancements.

3.1 Formulation of Control strategy

Each EV collects data (battery usage, energy consumption, driver behavior, charging patterns) and trains a lightweight local AI model. Instead of sending raw sensor/vehicle data to the cloud, only the model parameters are uploaded. Twofold voltage boost factor, excellent stability, and fewer power conversion stages are the benefits of the MISO converter [21-24]. To design the decoupler for the Multi-Input Single-Output (MISO) converter, it is crucial to obtain the averaged small-signal model of the converter in each operating mode.

$$\begin{cases} x\ (t) = A_c x(t) + B_c u(t) \\ y(t) = C_c x(t) \end{cases} \qquad (1)$$

where the state, input, and output vectors are denoted by x(t) ∈ ℜn1, u(t) ∈ ℜr, and y(t) ∈ ℜp, respectively. The dimensions of the Ac, Bc, and Cc matrices are n1×n1, n1×r, and p×n1, respectively. The discretized version of equation (1), as shown below, is taken into consideration for the controller design since discrete MPC techniques use discrete models for prediction.

$$\begin{cases} x_d\ (k+1) = A_d X_d(k) + B_d u(k) \\ y(k) = C_d x_d(k) \end{cases} \qquad (2)$$

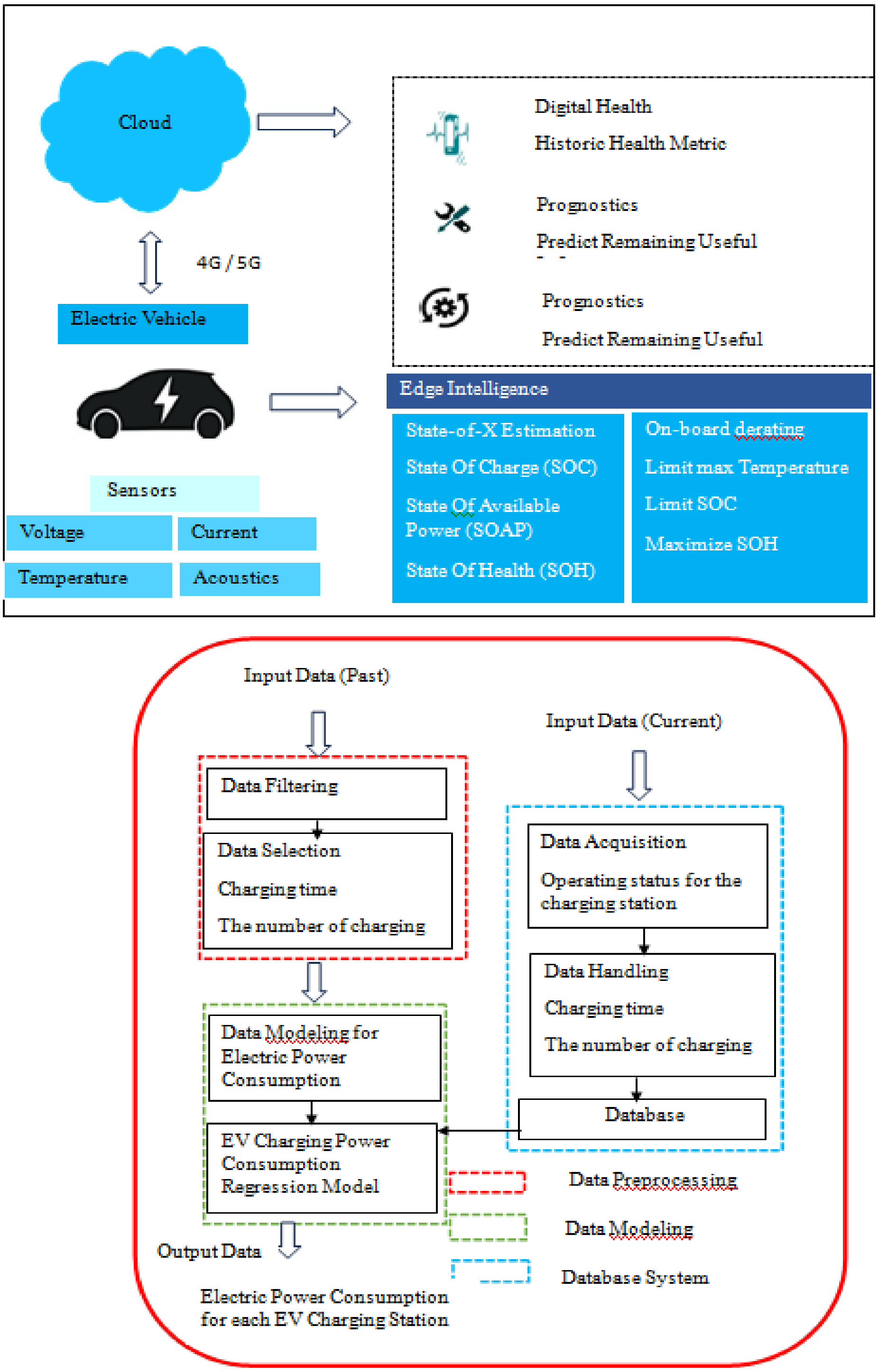


Fig. 4. Flow Diagram of IoT in Electric Vehicle

In order to create an augmented system that allows the predictive control system to monitor reference signals without steady-state errors, integrators are embedded into the system given by equation (2) [87]. The model of the enhanced state-space is provided by:

$$\begin{cases} X(k+1) = Ax(k) + B\Delta u(k) \\ y(k) = Cx(K) \end{cases} \qquad (3)$$

Using the state variables and incremental control variables, respectively, as:

$$\Delta u(k) = u(k) - u(k-1)$$

$$\Delta X_d(k) = x_d(k) - x_d(k-1)$$

The expected state and output variables are given by:

$$\begin{cases} x(k+m/k) = A^m x(k) + \sum_{j=0}^{m-1} A^{m-j-1} B\Delta u(k+j) \\ y(k+m/k) = CA^m x(k) + \sum_{i=0}^{m-1} CA^{m-j-1} B\Delta u(k+j) \end{cases} \qquad (4)$$

Defining the vectors Y and Δ U as:

$$Y(p^p \times 1) = [y(k+1/k)^T, Y[K+2/K)^T, \ldots.Y(k+p/k)^T]^T$$

And

$$\Delta U_{(rM\times 1)} = [\Delta u(k)^T, \Delta u(k+1)^T, \ldots.\Delta u(k+M-1)^T]^T$$

The prediction and control horizons, denoted by P and M, respectively, are explained in more detail in a subsequent section. For simplicity in notation,

$$Y = Gx(k) + H\Delta U \qquad (5)$$

Where

$$G = \begin{bmatrix} CA \\ CA^2 \\ \ldots \\ \ldots \\ CA^P \end{bmatrix}_{(pP\times n)} \quad \text{and } H = \begin{bmatrix} CB & 0 & 0 & \ldots & 0 \\ CAB & CB & 0 & \ldots & 0 \\ CA^2B & CAB & CB & \ldots & 0 \\ \ldots & \ldots & \ldots & \ldots & 0 \\ \ldots & \ldots & \ldots & \ldots & 0 \\ CA^{P-1}B & CA^{P-2}B & \ldots & \ldots & CA^{P-M}B \end{bmatrix}_{(pP\times rM)}$$

The goal of minimizing the differences between the reference signals and the expected outputs with the least amount of control effort is connected to the ideal incremental control law that is produced by minimizing a predetermined performance metric.

The cost function that represents the goal of control is constructed as:

$$J(K) = \sum_{m=1}^{P} \| y(K+m/K) - y_{ref}(k+m) \|_Q^2 + \sum_{m=0}^{M-1} \| \Delta u(k+m) \|_R^2 \qquad (6)$$

Positive definite tracking error and control effort weighting matrices are denoted by Q ∈ ℜpP×pP and R ∈ ℜrM×rM, respectively. Weight R penalizes the usage of control action, while elements of Q penalize the controlled outputs' departure from their reference values. The incremental control law that results is:

$$\Delta U = (H^T Q H + R)^{-1} H^T Q (Y_{ref} - Gx(k)) \qquad (7)$$

Note: The Hessian matrix of LMPC strategy is the matrix ξ = (H^TQH+R)^{-1}. λmax (ξ) λmin (ξ) (ratio of maximum to minimum singular values of ξ) is the condition number of the Hessian matrix, which is a measure of system ill-conditioning.

Federated Learning is a distributed machine learning approach where local devices (EVs, charging stations, traffic nodes) train AI models on their own data, and only the model updates (weights/gradients) are shared with a central aggregator (cloud/edge server). Raw data never leaves the devices. Let $F_{Fr} = F_1, F_2, \ldots \ldots F_n$ be the normalized features, where n is the length of features Then, the computation of weighted features is as follows:

$$NF_{Fr} = F_{Fr} \times W_{Fr} \qquad (8)$$

In the above equation, NF_{Fr} represents the new features, and W_{Fr} represents the weight function to be used to scaling the features.

The details of its construction are as follows:

$$a_1^1 = \sum w_i x_i^1 + \sum w_h^1 x_h^1 + w_c^1 s_h^{-1} \qquad (9)$$

$$b_1^t = f(a_1^t) \qquad (10)$$

The forget gate's input consists of the same three components as that of the input gate. The formula for the input vector of the forget gate at time t and the output vector produced by the excitation function f is as follows:

$$\mathrm{a}^t = \sum_{i=1}^{i} \binom{n}{k} x^k a^{n-k} + \sum_{h=0}^{H} W_h b_h^{t-1} + \sum_{c=1}^{C} w_c s^{t-1} \qquad (11)$$

$$b^t = f(a^t) \qquad (12)$$

The Cell unit receives two types of input: the input layer's input vector and the output gate's output from the preceding hidden layer. The formula to be used for this unit is as follows:

$$a_c^t = \sum_{i=1}^{I} w_{ic} x_i^t + \sum_{h-1}^{H} w_{hc} b^{t-1} \qquad (13)$$

$$a_c^t = b^t s_c^{t-1} + b_l^g (a_c^t) \qquad (14)$$

The output gate generates an output that consists of three components: the output vector from the input layer neurons, the output vector from the previous hidden layer's Cell, and the data currently reserved for the Cell.

$$a_w^t = \sum_{i=1}^{I} W_i^w x_i^1 + \sum_{h=1}^{H} W_h^w b_h^{t-1} + \sum_c^C W_c^w s^{t-1} \qquad (15)$$

Lastly, the following is the output vector formula for the Cell unit. The formula's excitation function is denoted by H:

$$b_c^t = b_w^t h s_c^t \qquad (16)$$

For enhancement, we fine-tuned the weight function with the proposed RCNN model. RPN features a regressor and a classifier. The concept of anchoring has been introduced by the authors. The anchor is the pivot point of the sliding window. The ZF Model, which builds on AlexNet, has dimensions of 256-d, whereas VGG-16 features dimensions of 512-d. The classifier assesses the likelihood of a proposal containing the target item. Regression is applied to regress the coordinates of the recommendations. Scale and aspect ratio are two essential properties for any input.

$$\textit{aspect ratio} = {\textit{width of input}}/{\textit{height of input data}} \quad (17)$$

reduce inter-class similarities by differentiating between normal and abnormal video portions [9-10].

An efficient technique for text-independent speaker recognition is put forward in this system. It improves text-independent speaker identification performance and has the ability to function in noisy environments. The process of feature extraction involves taking little bits of information from the voice signal and using it to identify each speaker. The discrete wavelet transforms serves as the foundation for the suggested plan. It is a kind of tool used in signal processing [15]. It can be used to obtain the frequency spectrum and is based on the multi-label resolution technique. It is more advantageous than DFT since it can analyze various speech parts at various scales and is limited in both time and frequency, whereas the Fourier transform is just limited in frequency.

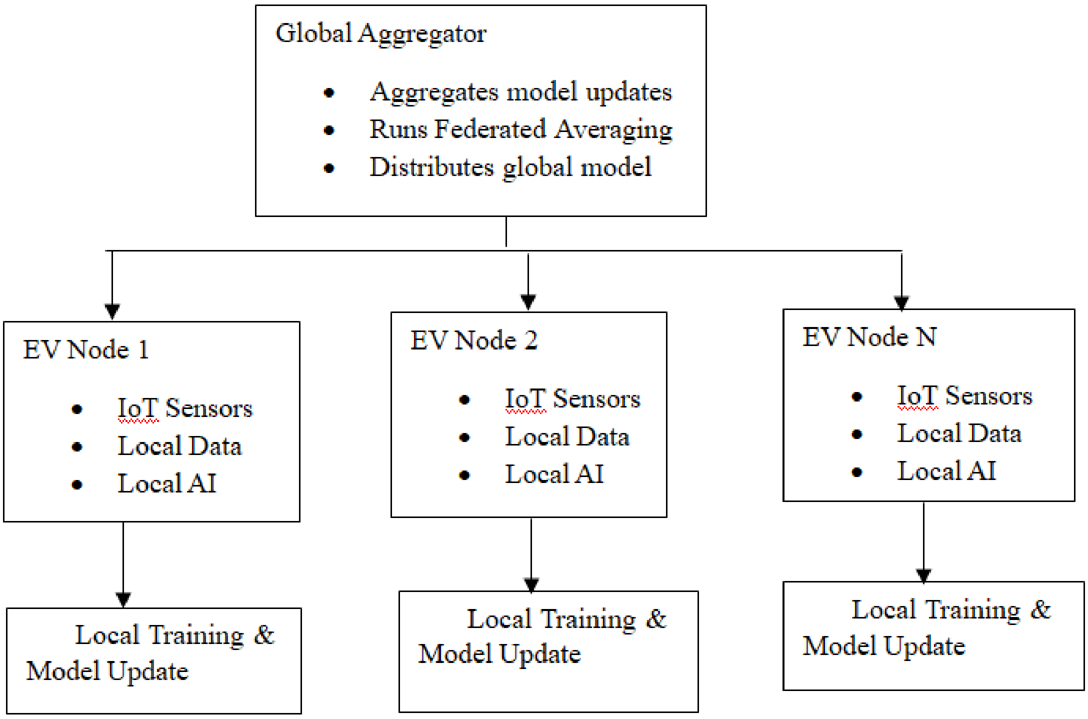


Fig. 5

AI algorithms enhance decision-making capabilities, enabling vehicles to adapt dynamically to changing environments and driving conditions. Moreover, the integration of AI with IoT in vehicles enhances user experience through personalized services and intuitive interfaces, fostering a seamless interaction between drivers, vehicles, and their surroundings. With the automotive sector advancing towards self-driving vehicles, these technologies set the stage for transportation systems that are safer and more efficient. However, ensuring cybersecurity measures remain paramount to safeguardagainst potential threats to vehicle data integrity and user privacy. Ultimately, the synergy between Big Data, AI, and IoT in advancing remote vehicle access signifies a transformative leap towards smarter, more connected automobiles capable of meeting the demands of modern mobility challenges [16].

4. RESULT AND DISCUSSION

This research demonstrated the increasing significance of AI-driven strategies for resolving internal EV energy management issues. Nonetheless, due to the challenges of incorporating renewable energy into the grid and the need to manage charging infrastructure to intentionally boost EV uptake, most studies have focused on hybrid setups or external energy management strategies. External energy management solutions, such as V2G systems, directly tackle grid stability and peak demand issues, making them noteworthy and vital for enabling the extensive deployment of EVs. Research has highlighted hybrid configurations as they provide a transitional solution from internal combustion engines (ICE) to fully electric vehicles (EVs), offering immediate emissions reductions by utilizing existing technologies.

Table 1

Metrics / KPIs	RBCM	MPC	Heuristic	FLC	Blockchain	Proposed IoT+AI
Energy Consumption Reduction (%)	8	12	14	13	15	18
Charging Delay Reduction (%)	7	14	17	15	18	25
Battery Utilization Improvement (%)	9	15	16	14	18	20
Driving Safety Enhancement (%)	5	10	12	11	13	30
Renewable Energy Integration (%)	10	18	20	17	25	40
Data Acquisition Rate (Hz)	80	120	140	130	150	200
Processing Latency (ms)	150	100	200	90	110	50
Prediction Accuracy (%)	65	80	82	78	85	92
System Scalability (EVs)	300	500	600	550	700	1000
User Satisfaction (%)	60	70	72	68	75	85
Energy Efficiency Ratio	0.65	0.75	0.78	0.72	0.80	0.88
Charging Efficiency Ratio	0.70	0.80	0.82	0.78	0.85	0.91
Battery Health Index	0.70	0.85	0.87	0.82	0.88	0.95
Safety Incident Rate (/1000 km)	0.12	0.08	0.07	0.09	0.06	0.02
Renewable Energy Contribution (%)	12	20	22	19	28	42

The specifics and difficulties of pure EVs, particularly with regard to their internal energy management system (EMS), were not covered by the analysis of the aforementioned options. The sole source of energy storage and distribution for pure EVs is batteries. To optimize battery life, manage energy consumption in real-time, and enhance vehicle performance under various driving conditions and driver requirements, pure EVs lacking hybridization require a sophisticated system. This study fills those gaps by offering a thorough investigation of AI-driven EMS methods used for internal energy management in pure EVs [17]. Various AI strategies pertinent to pure EVs, such as machine learning, reinforcement learning, and neural networks, will be highlighted and discussed in detail in this review. Their roles in enhancing energy distribution for better vehicle performance and battery lifespan will be specified.

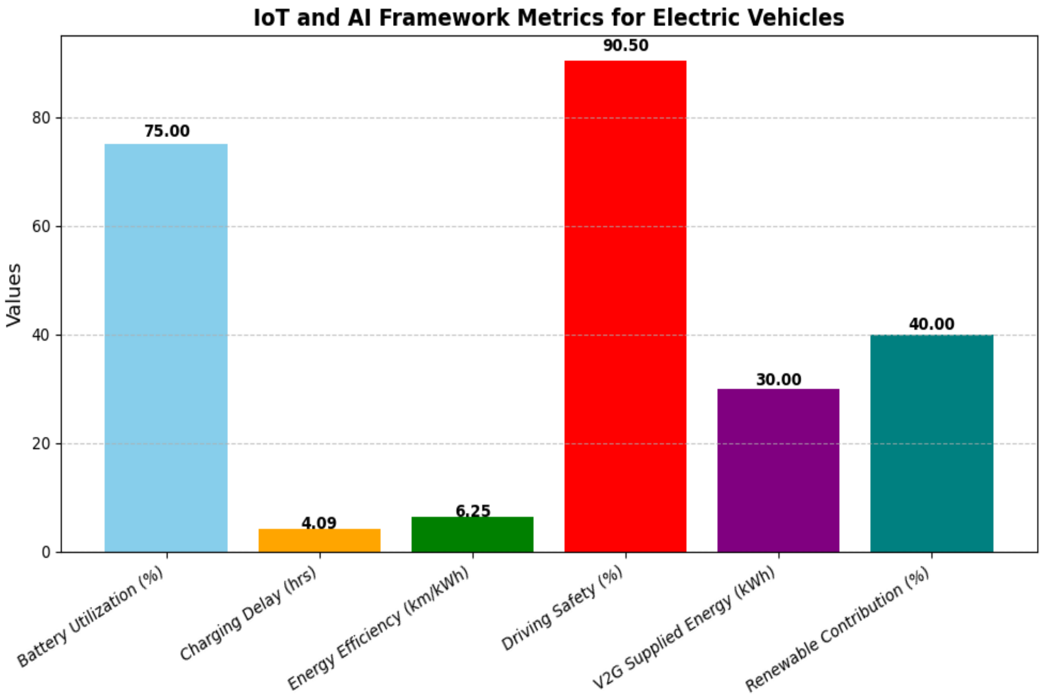


Fig. 6

Charging methods that utilize AI enhance energy distribution in EV charging networks and stations by employing dynamic data pertaining to vehicles and the environment. There is a growing trend in the utilization of DRL models, especially DDPG and multi-agent DRL methods, to improve the efficiency and dependability of charging procedures [18-20]. Thanks to these tactics, real-time reactions to alterations in needs, grid conditions, and car battery statuses become possible. This results in a reduction of operating costs and peak loads while optimizing the use of renewable energy sources. Another decentralized method that maintains privacy during the management of charging across various EVs and charging stations is Federated Reinforcement Learning (FRL). For electric car fleets, scalable, cooperative charging management is made possible by the emphasis on multi-agent systems.

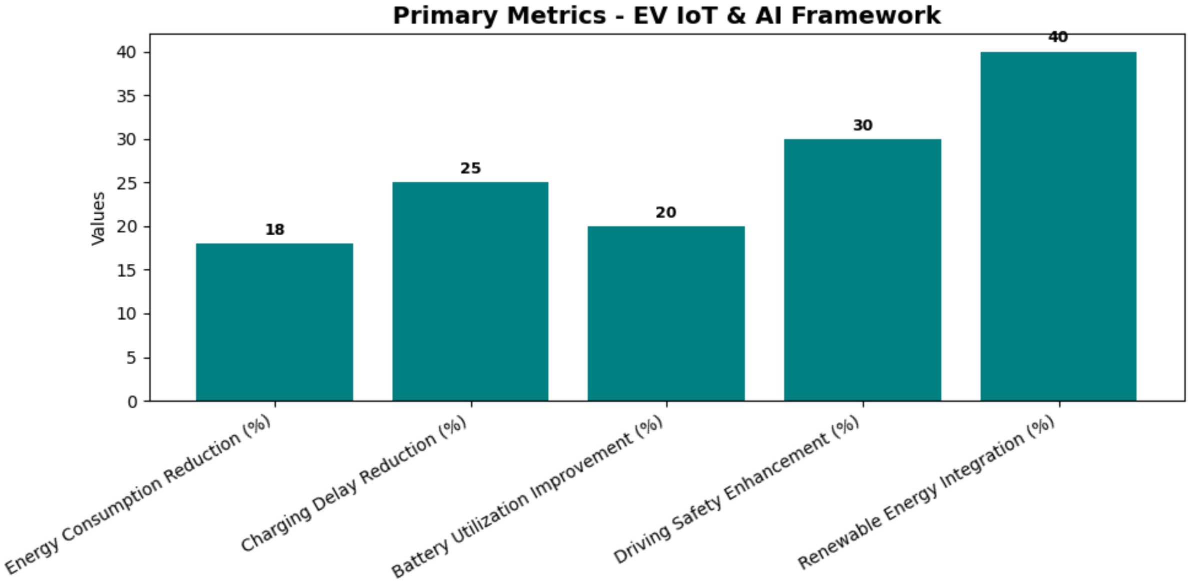


Fig. 7

It improves load balancing, which makes it especially advantageous for tackling issues with grid stability and lowering charging station energy costs. Machine learning methods, DRL, and multi-agent systems are revolutionizing the management of EV charging schemes by facilitating real-time and adaptable energy distribution across various environments. These models enhance energy distribution by balancing load demands, minimizing peak power, and increasing efficiency at both individual EV charging stations and across broader dispersed networks. For instance, approaches like DDPG and FRL promote cooperative, decentralized energy management by lowering expenses and improving grid stability [21-23]. These methods are well-suited for next-generation EV charging systems in urban and industrial areas because of their flexibility, scalability, and capability to manage dynamic environments with large amounts of data.

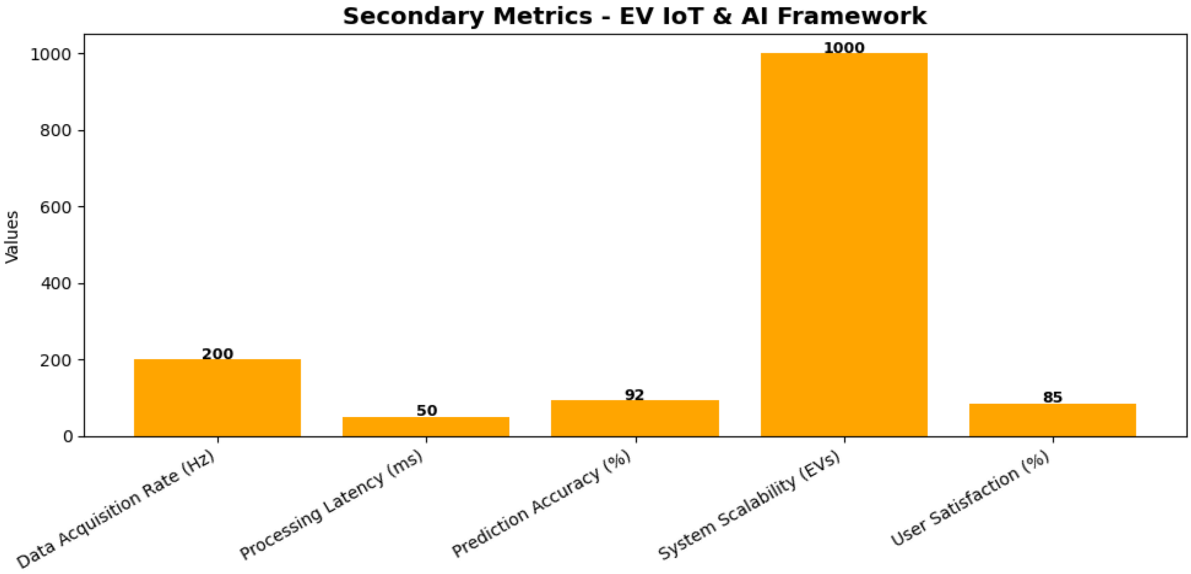


Fig. 8

The investigation includes a detailed analysis of the many IoT and AI applications in EVs, emphasizing how they enhance vehicle efficiency and performance. Additionally, the study carefully examines the opportunities and difficulties of incorporating IoT and AI into the EV ecosystem, providing insightful information about the potential effects and future prospects of these technologies.

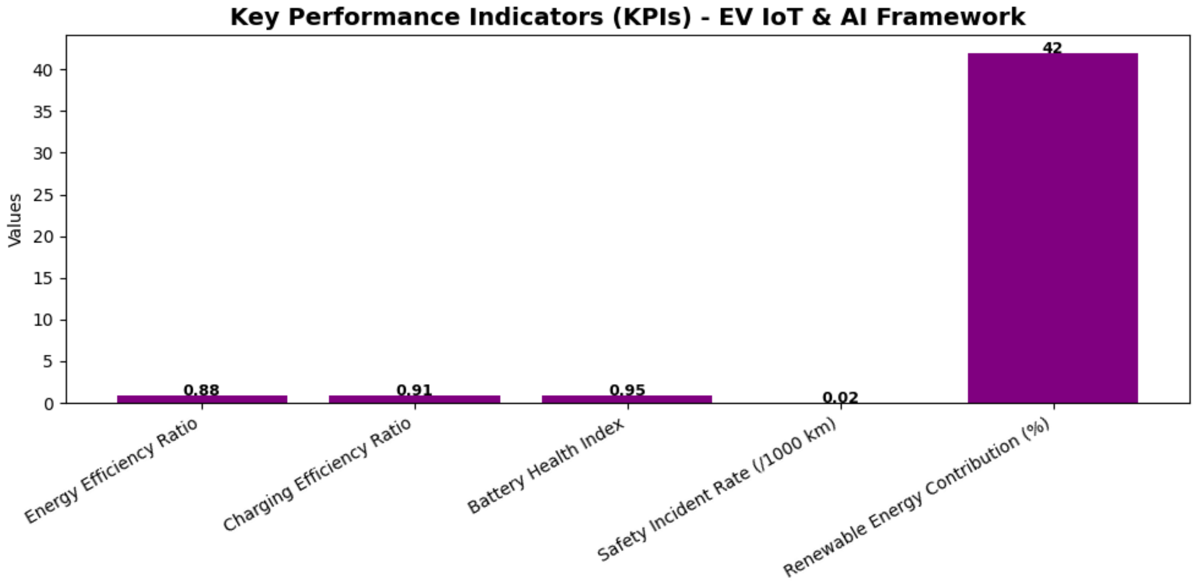
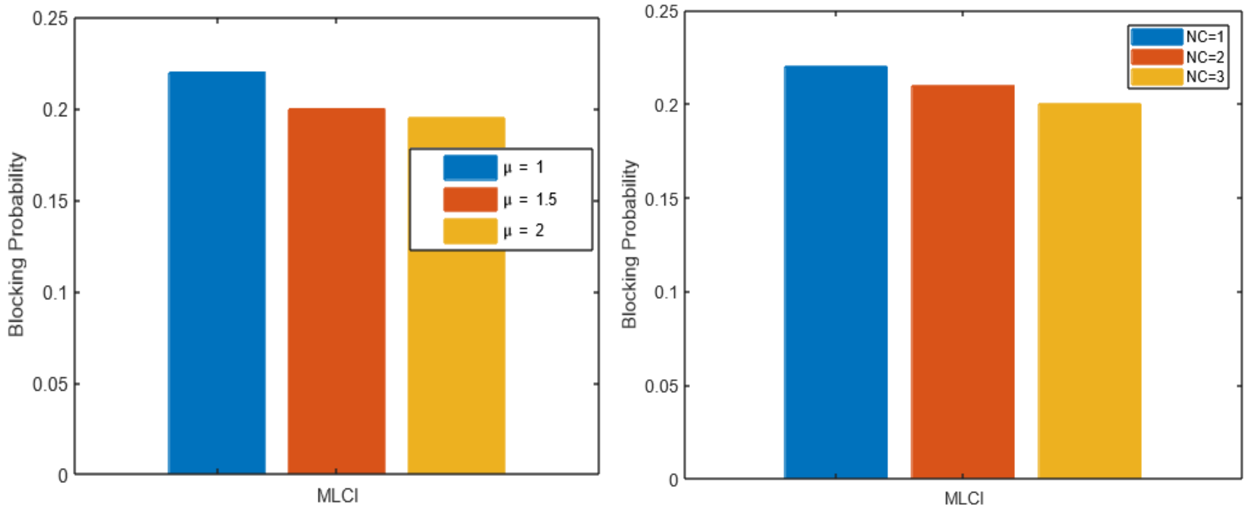


Fig. 9

The paper seeks to offer a complete knowledge of how IoT and AI are changing the electric mobility scene through in-depth study and discussion, ultimately opening the door for more sophisticated, effective, and sustainable transportation solutions. In order to tackle major difficulties affecting not only the automotive sector but also society at large, it is essential to integrate Internet of Things (IoT) and artificial intelligence (AI) technologies into electric vehicles. Your proposed model is superior overall because it incorporates IoT for real-time data collection and AI for predictive analytics and adaptive control [24]. This combination allows for higher efficiency, safety, scalability, and sustainability compared to traditional or even Blockchain/MPC models that focus only on specific aspects.

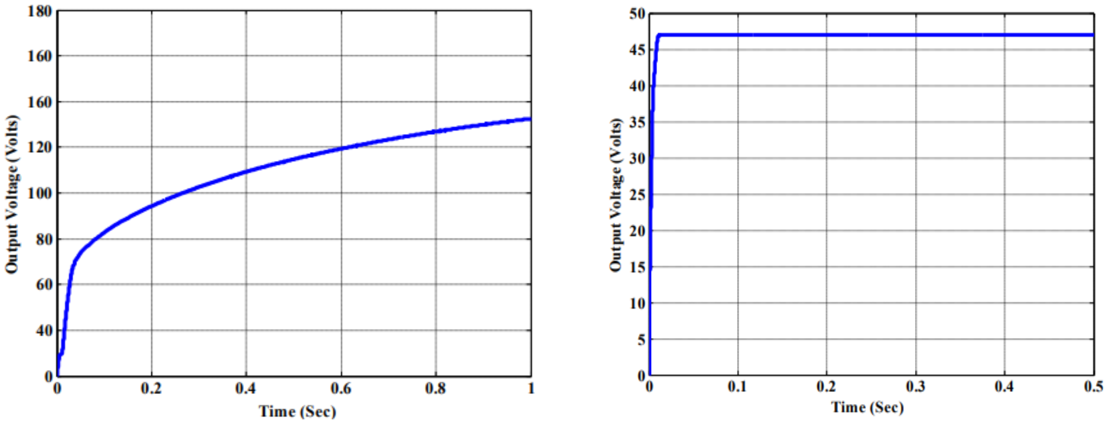
The proposed converter's input and output voltages are displayed in Figure 11 (d). The input voltage is 100V, and the output voltage archives 47 V, indicating that the converter's buck or discharging operation in the MPC-SAC controller operates efficiently and with less ripple than the previously suggested converter.



(a) (b)

Fig. 10. a) EVs Blocking Probability of charging mode b) EVs Blocking Probability of discharging mode.

The number of available chargers, the charging capacity of each charger, and the arrival rate of electric vehicles can all be taken into account when analyzing the blocking likelihood at a charging station with a variable number of chargers in a multi-level charging infrastructure. The blocking probability, or the chance that an EV won't be able to charge because a station is completely occupied, falls exponentially with the number of chargers. But when the number of chargers increases, the marginal drop in blocking likelihood decreases due to the law of diminishing returns [25]. Furthermore, the charging level also affects the blocking probability; Level 1 (slow) charging takes longer and increases the chance of blocking, whereas Level 2 (fast) and Level 3 (rapid) charging decrease the blocking probability because they require shorter charging times.



(a) **(b)**

Fig. 11. Simulation response of proposed controllers in charging mode and discharging mode

The simulated output voltage response of the suggested converter with MPC-SAC controller is displayed in Figure 11 a, where an output voltage of 150V is achieved.In contrast to the traditional Controller replies, the MPC-SAC response is composed of a fine response and is oscillation-free.

5. CONCLUSION

A revolutionary move towards sustainable mobility is represented by the electrification of transportation through the incorporation of IoT and AI technology in electric vehicles. The many ways that IoT and AI solutions can spur innovation, solve problems, and influence the direction of electric vehicle technology have all been covered in this article. We discover a world full with chances for innovation and disruption as we traverse the nexus of AI, IoT, and EVs. At the heart of this integration is the idea of smart mobility, in which EVs can communicate in real-time with the grid, infrastructure, and each other thanks to AI and IoT technology. AI systems evaluate information gathered from sensors installed in infrastructure and automobiles to optimize routes, control energy use, and forecast maintenance requirements. In the meantime, IoT devices enable smooth connectivity, allowing vehicle-to-everything (V2X) communication, over-the-air upgrades, and remote monitoring. Increased energy efficiency is one of the main advantages of integrating AI and IoT with EVs. In order to maximize range and reduce energy consumption, artificial intelligence systems optimize driving behavior by taking into account variables like traffic, weather patterns, and topographical characteristics. IoT sensors also keep an eye on the health and performance of batteries, allowing for proactive maintenance and extending battery life. By lowering energy use and emissions, these developments help individual EV owners as well as the sustainability of transportation systems as a whole. Additionally, EV safety and user experience are enhanced by AI and IoT technology. AI-powered advanced driver assistance systems (ADAS) evaluate sensor data to enhance lane keeping, help with parking manoeuvres, and identify and prevent possible collisions. Remote diagnostics and software upgrades are made possible by IoT connectivity, guaranteeing that EVs have the newest safety features and performance improvements. By customizing climate control settings, entertainment options, and vehicle settings to each driver's tastes and driving habits, AI-driven personalization features improve the user experience. The integration of AI, IoT, and EVs within smart cities and infrastructure creates opportunities for sustainability and optimization that have never been heard of before. Traffic management systems driven by AI analyze real-time traffic information to enhance flow, alleviate congestion, and lower emissions. The charging rates are adapted in real-time through the interaction between EVs and IoT-enabled charging infrastructure, considering user preferences, renewable energy availability, and grid demand. Through the two-way vehicle-to-grid (V2G) integration, electric vehicles (EVs) can function as flexible energy storage devices, facilitating the integration of renewable energy sources and enhancing grid stability. However, there are disadvantages and problems associated with the widespread implementation of AI and IoT in EVs. To guarantee that sensitive data gathered from EVs and sent across networks is protected, data privacy and security issues must be resolved. To facilitate smooth communication between various AI and IoT platforms, automobiles, and infrastructure elements, interoperability standards and protocols are required. Furthermore, to avoid making already-existing disparities in transportation affordability and access worse, fair access to smart mobility solutions must be guaranteed.

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