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Enhancing Electric Vehicle Performance and Connectivity through Internet of Things Integration

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Abstract: Internet of Things (IoT) technology in Electric Vehicles (EVs) has the potential to enhance performance, connectivity, and the overall user experience. This connection improves EV efficiency, battery life, user interaction, charging infrastructure, and traffic management systems. Dependable communication networks, system compatibility, and data security are all essential. Several concerns must be solved before manufacturers can use the IoT in EVs. Internet of Things-based Accurate Estimation Monitoring Analysis (IoT-AEMA) is presented in this paper as a solution to address these problems. Intending to enhance energy management, safety, and predictive maintenance, the IoT-AEMA has taken the initiative. Electric vehicle (EV) performance can be monitored comprehensively and in real-time with the help of IoT-AEMA, which utilizes IoT technology. This technology makes monitoring metrics like energy use and battery health more accurate. Proactive maintenance is made possible, and communication with smart infrastructure is improved. Improving electric vehicle (EV) connection and efficiency has never been easier than with this scalable solution that prioritizes sustainability. This objective will be accomplished by providing extensive analysis and monitoring of vehicle parameters in real-time. These applications use this technology to enhance data accuracy, the decision-making process for drivers and manufacturers, and the development of intelligent transportation networks. The effectiveness of IoT-AEMA has been demonstrated through simulation studies in various circumstances. By giving accurate insights and encouraging collaboration, this research implies that the electric vehicle industry is on the verge of experiencing a paradigm change. According to the information presented in this article, the IoT and advanced energy management have the potential to make EVs more dependable, efficient, and integrated into the infrastructure of smart cities. The proposed method increases the Energy Management Optimization ratio by 97.6%, Data Accuracy ratio by 90.2%, Predictive Maintenance ratio by 95.7%, System Compatibility ratio by 93.4% and Reliability Analysis ratio by 98.4% compared to other existing methods.

Introduction

One of the greatest issues with IoT-powered EVs is that they use traditional methods (Rimal et al., 2022). Traditional methods sometimes struggle with IoT integration's complexity and scale. The lack of defined communication protocols is a major barrier to the interoperability of the electric vehicle's many systems and equipment that cause these issues (LV et al., 2021).

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Traditional vehicle communication systems are unprepared to handle IoT device data quantities, causing latency and capacity issues, which originate from poor system design (Vaidya and Mouftah, 2020). Important concerns include maintaining the confidentiality of data and safeguarding personal information. Cyberattacks on connected automobiles are too advanced for current security solutions. Low processing power and storage capacity are other issues with vehicle control systems (Elghanam et al., 2021). These machines are not designed to handle real-time data processing and analytics for IoT applications (Kahveci et al., 2022). The integration procedure often raises electricity management concerns and IoT systems' impact on the EV infrastructure (Garrido-Hidalgo et al., 2020).

If this happens, vehicle handling and battery efficiency may suffer. Existing vehicle manufacturing methods cannot readily adopt IoT developments, prolonging development cycles and increasing operational expenses (Solanke et al., 2021). The IoT can easily incorporate new functionalities in automobile engineering, and IoT professionals are few, compounding these challenges (Florea and Taralunga, 2020). This insufficiency is one of the primary factors that contribute to the problem. The final point is that regulatory and compliance difficulties are additionally problematic (Bhaskar et al., 2022). Because electric vehicles connected to the IoT require new laws and regulations, present automotive standards do not meet their needs (Mahdavian et al., 2021). Solving these issues requires shifting from traditional tactics to more creative ones. This goal requires regulatory, technological, and automaker cooperation (Mierlo et al., 2021). The long-term goal is to develop an ecosystem capable of supporting connected electric vehicles in the future.

EVs using IoT technologies must overcome various challenges, which can hinder performance and relationship improvement (Mohd Aman et al., 2021). Due to their interconnectedness, electric vehicles are vulnerable to cyberattacks, making cybersecurity crucial; comprehensive cybersecurity must come first (Jiang et al., 2021). Enormous data demand appropriate processing and management systems, which strains the current infrastructure. Standardization across IoT devices and platforms complicates interoperability and smooth integration. Industrial companies and their customers may find the high costs of adopting complex IoT systems. Network latency and coverage in cities with low urban populations hinder real-time data transfer (Bhatti et al., 2021). IoT components must be sturdy and reliable to withstand vehicle abuse. Due to the large volumes of data EV drivers collect, rigorous privacy laws are needed. Integrating the IoT into EVs and boosting their performance and connection requires solving many problems.

The contributions of this paper are:

#Conducting accurate real-time monitoring and analysis to extend the life of electric car batteries and increase their efficiency using Internet of Things-based Accurate Estimation Monitoring Analysis (IoT-AEMA).

#Utilizing extensive data analysis to accomplish the objective of developing predictive maintenance and improving vehicle safety.

#Developing smart transportation networks that are required to determine how easily the EVs are integrated with the users, charging stations, and traffic control information systems by communicating with one another.

An examination of the literature presented in Section II acts as the basis for the subsequent inquiry that will be conducted. IoT technology should be included in EVs to improve performance and connectivity. The IoT-AEMA is an area of mathematics explored in Section III. Section IV contains the findings and discussion presentation, while Section V has an overview and the approved recommendations.

Related works

IoT technology rapidly expands and revolutionizes many industries, including the automotive and EV sectors. This is having a significant impact on both sectors. Researchers have explored many IoT applications to enhance electric and connected car user experience, connectivity, and overall performance. The IoT-based Centralised Control Strategy (IoT-CCS) (Islam et al., 2020) that was proposed by Islam, M. R. and colleagues, using the DE optimization algorithm, increases network performance, is less demanding on communication infrastructure, is convenient for owners of electric vehicles, and has a lighter data processing overhead.

Rahim et al. (2021) conducted a survey of IoT technology in the automobile industry. They provide an overview of its development, uses, benefits, and problems. Additionally, they suggest a conceptual framework that will guide future improvements in IoT technology in automotive systems. Das et al. (2020) comprehensively evaluated the EV market, charging infrastructure, and grid impact. Additionally, it will evaluate control structures and analyze future developments, offering optimization tactics for improved EV grid integration and energy Internet development.

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Damaj et al. (2021) surveyed the performance of Connected and Autonomous Electric Vehicles (CAEVs), produce a quality of experience taxonomy that includes quality indicators, and provide a framework to integrate quality of experience concepts to guide and accelerate the development of future CAEVs. Urooj et al. (2021) proposed IoT-based monitoring (IoT-bM) for electric vehicle battery life. This monitoring method uses Things Speak and a boosting algorithm, ultimately leading to a capacity gain of 74.3% and a reduction in implementation costs. The IoT-AEMA is much more efficient and effective than other currently used methods. The performance and cost-efficiency are both improved as a result.

Pal et al. (2023) proposed the Integrated Entropy-TOPSIS Approach for Electric Vehicle Selection. The purpose of this study was to examine the electric vehicle (EV) in the context of the Indian market and to use the TOPSIS method as an MCDM to determine which EV on the market in India is the best option for the consumer. The weights linked to the criterion are derived using the entropy approach. Thirteen different electric cars have been chosen as cases for this investigation. In addition to determining the best option among the current EVs, this research provides an actual preference order and considers various selection factors.

Bondu Pavan Kumar Reddy and Vyza Usha Reddy (2024) suggested the PV-Based Design and Evaluation of Power Electronic Topologies for EV Applications. Using and without the MPPT algorithm, this research describes the revamped SEPIC converter design. The author provides optimized parameter selection, design approach, and simulation methodologies to analyze converter performance in electric vehicle charging applications. The effects on the converter switching time under typical settings for testing solar PV panels are examined and contrasted between two MPPT methods, Perturb and Observe (P&O) and incremental conductance (IC). The system's performance can be thoroughly assessed by creating a MATLAB/Simulink model miming a 48 V, 200 Ah battery charging with a 2 kW solar PV input via the modified SEPIC converter. The model tracks changes in the battery's state of charge (SoC), voltage, and charging current. Highlighting the usefulness of the MPPT algorithms in optimizing gathered solar energy, the simulation results show that the battery SoC grows from 50% to 50.034% without MPPT and to 50.042% with MPPT under similar simulated circumstances (10 Sec).

Dontabhaktuni Jayakumar and Samineni Peddakrishna (2024) discussed the Performance Evaluation of the YOLOv5-based Custom Object Detection Model for Campus-Specific Scenario. An autonomous electric vehicle (AEV)-specific object detection model built on the YOLOv5 architecture is tested and shown to work adequately in this research. The model is prepared for training by applying pre-processing techniques to the data using the Roboflow computer vision platform's extensive set of capabilities. Pedestrians, cars, buildings, and obstructions were all part of the varied datasets used in the trials, designed to mimic campus-specific driving situations. A precision of 0.851, recall of 0.831, and mAP of 0.843 were the outcomes of the training procedure, which was carried out in a controlled setting.

Avanish Kumar (2020) deliberated the ADVISOR-Based Performance Analysis. Hybrid electric vehicles (HEVs) combine the best features of two types of powertrains: an electric motor and a more traditional internal combustion engine (ICE) to provide superior economy and more stable operation. The topological configuration of the drive train defines series and parallel HEVs. This research compares the performance of a tiny HEV in three different configurations: pure ICE, series HEV and parallel hybrid. The ADVISOR program is used with the Matlab/Simulink platform for simulation. Additionally, the author tested the acceleration performance and gradability, and we investigated the vehicle emissions to get the results.

Kaushik Das et al. (2024) presented the supervised machine learning for electric vehicle battery health performance. An algorithm for estimating the state of health from directly measurable voltage, current, and temperature indices has been developed using various machine-learning techniques. These algorithms include a noble random forest (RF) supervised K nearest neighbours (KNN), decision tree (DT), and support vector regressor (SVR). The goal is to eliminate inherited electrochemical characteristics such as voltage hysteresis, ageing, degradation level, and operational and environmental effects. This method works using data from batteries collected by Sandia National Laboratories. Using methods such as mean squared error (MSE), mean absolute per cent error (MAPE), mean absolute error (MAE), root mean squared error (RMSE), and this study may get the comparative features.

Hassan Khalid et al. (2023) introduced the overcoming challenges and enhancements for static and dynamic electric vehicle applications. To demonstrate their viability for both static and dynamic applications, the study details several magnetic coupler designs and how they were optimized to enhance overall magnetic coupling efficiency, pulsations, and the power null zone.

The article also emphasizes the need to be safe while setting up wireless power transfer systems, whether on roadways or in one's own house. Consequently, this analysis proposes revised standards from IEEE/SAE and IEC that analyze system and equipment requirements. The most practical option with LCC-S compensation is the DD with DDQ receiver coil, which provides the best electrical performance characteristics and an efficiency of 93% for current dynamic charging, according to the discussion. Lastly, to simplify control, it is proposed to use double-sided DD coils with voltage source output characteristics and LCC-S compensation.

Ramanathan Gopalasami et al. (2023) were hybridizing the super lift luo converter and boost converter for electric vehicle charging applications is recommended. A novel DC-DC multiport converter that combines a Super-lift Luo and Boost Converter (SLBC) with dual inputs for photovoltaic (PV) and battery sources has been suggested to overcome existing obstacles. The suggested DIDO converter uses two step-up voltages, one from the Luo converter and another from the Boost converter, to super-lift the input voltage, a major improvement over existing options. To achieve great voltage gain and power efficiency, the SLBC employs basic architecture without extra electric circuits or transformers.

Rabia Sehab et al. (2023) suggested the Super-Twisting Sliding Mode Control to Improve the Performances and Robustness of a Switched Reluctance Machine for an EV Drivetrain Application. Given the highly nonlinear nature of SRMs, this work aims to compare the robust controllers constructed in terms of performance and resilience. The control strategy's velocity and current control loops use SMC and STSMC, two types of SMC, which are created and verified by simulation. Nonetheless, their efficacy is tested compared to traditional PI controller-based classical control. The author can compare their resilience by simulating changes to the SRM parameters with each of the three controllers. Finally, the best controller for electric vehicle applications, Super-Twisting Sliding Mode Control (STSMC), is shown by experimental validation on a constructed test bench employing all three controllers.

Min Hua et al. (2023) proposed the Energy management of multi-mode plug-in hybrid electric vehicles using multi-agent deep reinforcement learning. A multi-agent deep reinforcement learning (MADRL) based MIMO control approach for energy management of the multi-mode PHEV is studied in this work to optimize the vehicle on a global scale. To facilitate collaboration between two learning agents inside the MADRL framework and the deep deterministic policy gradient (DDPG) algorithm, a hand-shaking approach is suggested, which involves the introduction of a relevance ratio. By doing a sensitivity study on the elements that impact learning performance, the author can achieve unified settings for the DDPG agents. Using a parametric analysis of the relevance ratio, we find the best way to implement the hand-shaking approach. On a software-in-the-loop testing platform, the suggested energy management strategy is shown to have an advantage. The research found that their learning rate is the most important aspect of DDPG agents' learning performance.

Yuvaraj et al. (2023) investigated the EV Charging Stations and DSTATCOM in Practical Indian Distribution Systems Using the Bald Eagle Search Algorithm. The distribution static compensator (DSTATCOM) and the DS, which is connected to the charging station, collaborate to reduce the effect of the EVCS. The most efficient distribution of DSTATCOM and EVCS throughout the DS was determined using a novel optimization method based on the Bald Eagle Search Algorithm (BESA), which draws inspiration from nature. The 28-bus and 108-bus distribution networks in India have been evaluated to see how well the suggested method reduces actual power loss. Maximizing the system's net savings, voltage stability, and bus voltage may be achieved by minimizing power loss. The results of the test cases demonstrate that, in the DS, the optimization based on BESA is superior to the optimization based on BA in terms of reducing power loss, increasing bus voltage, and improving yearly net savings.

Materials and Methods

The IoT-AEMA is a suggested system that uses the IoT to improve EVs' user experience, connection, and performance. Using real-time data from car sensors, storage on the internet, and sophisticated analytics, IoT-AEMA optimizes energy administration, improves safety and facilitates scheduled servicing to guarantee consistent and effective EV operations.

The Figure can be used to observe the suggested system design. A solar photovoltaic (PV) panel, charging infrastructure, suggested Battery Management System (BMS), and IoT app make it up. When exposed to sunshine, the PV panel produces direct current voltages and sends them to the power grid. As seen in Figure 1, an EV charging station and microprocessor charge the engine's Lithium-ion battery. A battery is required to store the initial energy for the PV source. Since PV isn't

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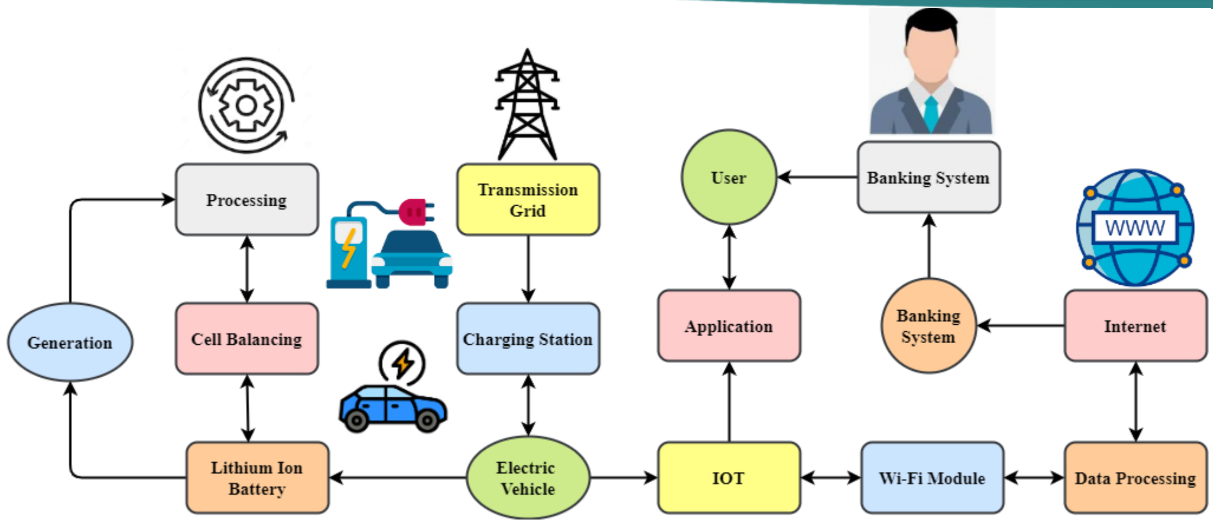

Figure 1. Diagram depicting the components of an EV battery management system.

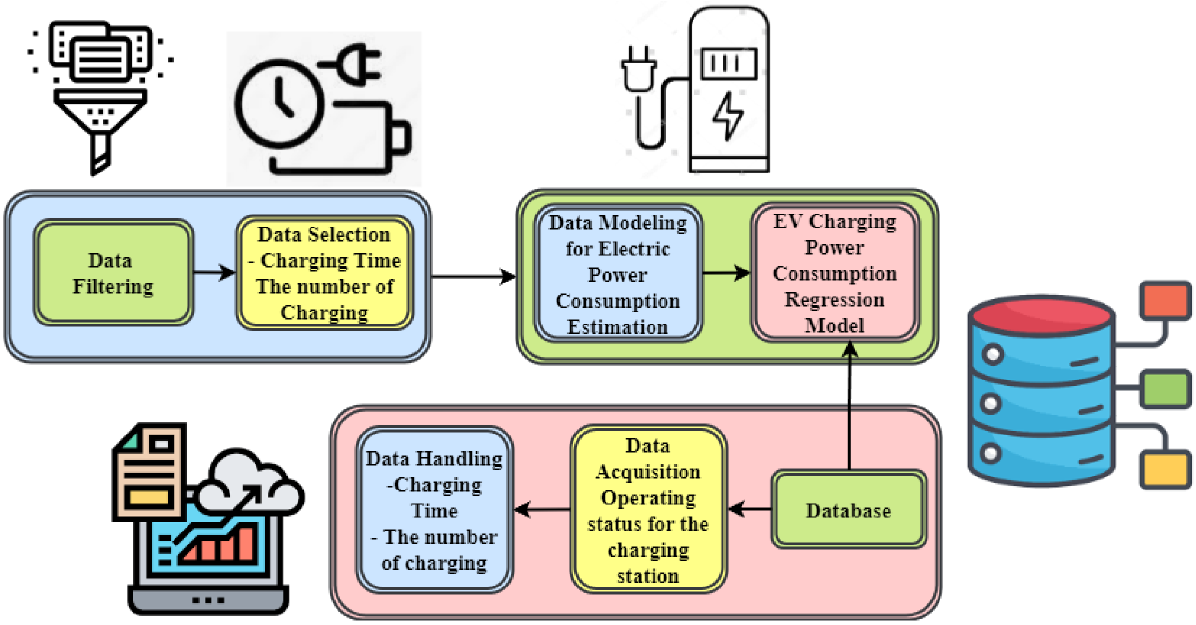

Figure 2. Schematic of the planned system's components. Electric vehicle: EV

as efficient as fossil fuels, it needs to be stored when the sun doesn't shine.

Therefore, it will be utilized when stored in the battery when needed. The BMS's principal role in EVs is to monitor key metrics such as battery life, charging phases, capability, voltage, temperature, state of the driver's seat consumption of energy, remaining runtime, and operating time. Employing a specialized user interface, the created system may provide electric vehicle owners with up-to-the-minute details on the closest charging station that offers the most efficient and cost-effective charging options and a safe online method for viewing the EV's current battery status.

$$K(v) = \int_{\partial}^{1}\big((\forall p)^2 - R(v)\big)ez \quad \partial w \ \equiv P_0^3 \ (\forall) \tag{1}$$

The suggested IoT-AEMA method's control of energy is affected by the interaction between different vehicle parameters $(\forall p)^2$. In this case, the energy management measure is written as $K(v)$, the performance measurements are represented by P_0^3 $(\forall)$, the barriers or inefficiency are written as $R(v)ez$, and the efficiency coefficient integrated across the variable ∂w is written as e denoted in Equation (1).

$$\frac{x}{n+\partial} - \frac{d_0+r(b)}{n} \geq q^*(x) \geq \frac{x}{v} \ for\ all\ \propto > U \tag{2}$$

This Equation (2) is relevant to the IoT-AEMA approach because it limits the electric vehicle system's efficiency $\propto > U$ and performance measures $q^*(x)$). In this case, x stands for the variable that is input, n and ∂ represents the system parameters, d_0 and $r(b)$ deal with the initial and resistant factors, and v is a performance component.

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The suggested system's structure is shown in Figure 2. The system's bulk comprises the data analysis, simulation, and processing modules. The input data for the estimating model is processed in the data preparation stage. The data processing unit generates a model that can predict electricity usage based only on charging time and number. The computerized database part receives real-time data about car charging stations and uses it to build a database that calculates electric power use. The suggested system uses location and real-time data to track how much electricity each charging station uses. A malfunctioning charger or a data storage or transfer mistake might lead to distorted data from the real charging station. These could severely impact the creation of the electric power consumption estimate model. Consequently, this stage eliminates errors in preparing the data to be included in the estimating model of electricity use before the data is used in the modelling process.

$$q*(x) = b \leq dr(b) - sp + b\,(c-1)m(u-w) \tag{3}$$

By outlining the performance measure $q*(x)$ Equation (3) aligns with the IoT-AEMA technique regarding several impacting elements. This is where b stands for baseline performance, $dr(b)$ is a constant resistance factor, sp is a parameter of the system, and $b\,(c-1)$ takes into consideration changed variables, including effectiveness adjustments (c), mass (m), and the environment $(u-w)$.

$$\int_{\infty}^{1} d(y) - H(p-k) + (y)dz > \frac{1}{n+s_1} - \int_{\propto}^{1} z^2 \tag{4}$$

The system-specific adjustment is denoted by $H(p-k)$ and the variables impacting performance are y and z. The differential parameter $(\infty, 1)$ is represented by the Equation (4), z^2. Because of this disparity dz, know that these variables' combined impact on performance indicators will always be more than a certain threshold $n+s_1$on Energy Management Optimization Analysis.

The schematic of the suggested system is seen in Figure 3. The system's bulk comprises the data evaluation, modelling, and pre-processing modules. The input data for the estimating model is processed in the data preparation stage. With only the duration of the charge and the total number of charges, the data modelling unit may create a model that can predict electric power usage. By obtaining real-time data on car charging stations, the database system division builds the database that calculates electric power usage. The proposed system uses location and real-time data to track how much electricity each charging location uses. In the event of a charger malfunction, data transfer or storage mistake, the real data from the charging station can be inaccurate. These could severely impact the creation of the power consumption estimate model. Consequently, this stage eliminates mistakes in preparing the data to be utilized in the estimating model of power use when the raw data is used in the modelling process.

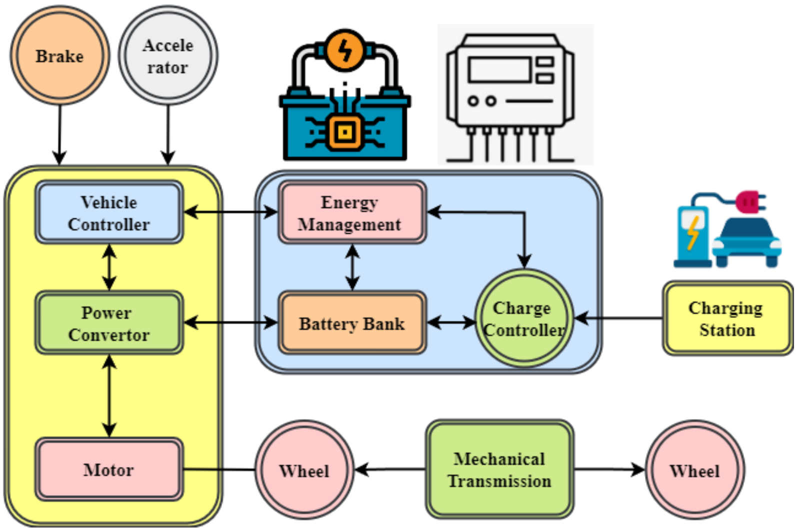

Figure 3. A schematic depicting the major components of a standard PEV system.

$$\int_{\partial}^{1} x(z-1)H(q-1)df > \frac{1}{n-d_2} - \int_{\partial}^{2} (y)dw \tag{5}$$

Equation (5) shows the equilibrium of the many variables $(n-d_2)$impacting the functioning of the EV system. Adjusted performance metrics are represented by $x(z-1)$ and $H(q-1)$ in this context, whereas differential variables reflecting the system's settings are denoted by (y) and df and dw on data accuracy analysis.

$$g(q-1) < \frac{1}{2}\left[\frac{1}{n-\forall} - \frac{1}{n-s_e}\right]||n||e_e^{w-1}(d-q) \tag{6}$$

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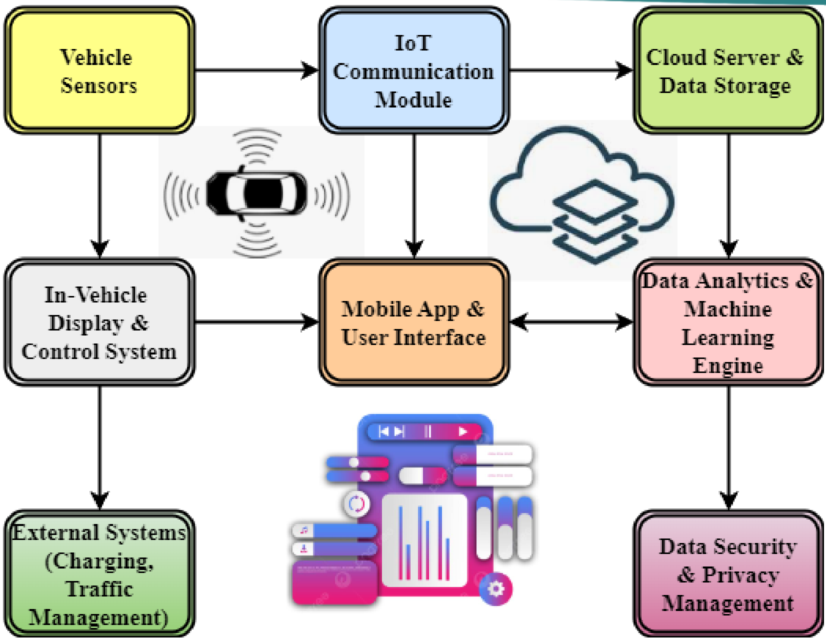

Figure 4. IoT-Based Electric Vehicle System Design.

Based on system settings and external conditions ∀, the efficiency function $g(q-1)$ is constrained by the Equation (6). The modified performance metric is represented by, in this context, the system variables n and s_e respectively, the exponential influence of the environment is e_e^{w-1} and the resulting variation of performance is $d-q$ reflected on predictive maintenance analysis. A Plug-in Electric Vehicle, or PEV, is a vehicle that can be charged while driven. Charging this car by connecting it to a power outlet or a charging station is possible. Plug-in hybrid electric vehicles (PHEVs) combine a standard gasoline engine with an electric motor; Battery Electric Vehicles (BEVs) are all-electric vehicles. A plug-in electric vehicle's (PEV) capacity to recharge itself is its defining feature, as opposed to more conventional cars that use fossil fuels exclusively.

The design of an EV system that incorporates the IoT is shown in Figure 4, which highlights how different parts work together to improve the EV's performance, connection, and user experience. For the vehicle's functionality and security, sensors track vital metrics like battery life, temperature, and pressure in real-time. This data is communicated via the IoT communications module, which utilizes Bluetooth, Wi-Fi, and cellular networks to ensure effective data flow to other system components. Safe and flexible data management is made possible by sending the data to a server in the cloud, where it may be stored and processed further. Using automated alarm systems, predictive analytics, and real-time data monitoring, the suggested IoT-AEMA strategy guarantees safety. IoT sensors constantly monitor vital signs like battery life, temperature, tyre pressure, and object proximity. To promptly notify the driver and system administrators, this data is evaluated using sophisticated algorithms that identify any irregularities or possible dangers. Integrating secure communication protocols further improves operations and cybersecurity by protecting data integrity and preventing cyber attacks.

A driver may monitor the vehicle's health and adjust its settings using an in-vehicle screen and control system, providing real-time data from the sensors to help them drive more safely and efficiently. A mobile app further improves user involvement by facilitating remote vehicle monitoring and control, alerting the user, and showing pertinent data. A data machine learning and analytics engine analyses the gathered data, producing useful insights, forecasts when maintenance will be required, and optimizes the vehicle's performance using sophisticated algorithms. The design incorporates third-party services for optimal integration with its natural setting, including charging and traffic control infrastructure. Using strong privacy and security data management strategies, the system ensures that all data, whether transported or stored, is secure and private. Full IoT integration in electric vehicles is a prime example of how cutting-edge tech can improve a vehicle's functionality, connection, and user experience.

$$\frac{e}{dw} - g\left(v_{f-1} + e_w\right) = \int_v^1 \left(q * (w_1 + f_z) - E(H_z - 1)\right) \quad (7)$$

Equation (7), $(q * (w_1 + f_z))$ describes the link between the conservation of energy $\frac{e}{dw}$, system modifications ($v_{f-1} + e_w$)), and the IoT-AEMA approach. In this case, the rate of change $(v, 1)$ in energy use is represented by $(q * (w_1 + f_z))$, system-related modifications are denoted by $E(H_z - 1)$, and the accumulated performance effect is captured by the integral of System compatibility analysis.

$$\int_e^1 E\, d_{f(n+1)} = \int_z^1 (yw_z - (df+1)dz) + (aV^{w-1} + na^2) \quad (8)$$

Efficiency $(e, 1)$ and adjustment variables $(z, 1)$ are included in the energy efficiency (E) and dynamics of systems $(d_{f(n+1)})$ Equation (8). In this case yw_z, the entire effect on energy efficiency is shown on $df+1$, while the performance impacts aV^{w-1} and adjustment variables na^2 are balanced on reliability analysis.

By offering accurate real-time monitoring and thorough analysis of several vehicle metrics, IoT-AEMA presents an opportunity for the EV ecosystem. This technology improves the reliability, efficiency, and integration of electric vehicles into the infrastructure of smart cities by enhancing decision-making skills for both drivers and designers. It helps to construct intelligent public transit systems.

Result and Discussion

The reliability, interoperability, predictive maintenance, data accuracy, energy management optimization, and other important studies are discussed in this introduction. To help enhance smart and sustainable transport networks as a whole, each study focuses on a different set of problems and opportunities. The simulator includes essential IoT components such as advanced sensors, connectivity modules, and a data processing framework that resembles real-world EV operation circumstances. Accurate simulation of EV characteristics, such as battery charge, energy consumption rates, and thermal performance, under different driving situations becomes possible in this virtual environment. Integrating with the cloud for sophisticated analytics and storage and edge computing capabilities for local processing are crucial simulator setups. Due to the system's ability to provide Vehicle-to-grid (V2G) connection, testing the effects of various connectivity features on smart grid integration can be conducted. Various scenarios, including urban and highway travel, different weather conditions, and varying loads, were included to verify the dependability and scalability of IoT-AEMA.

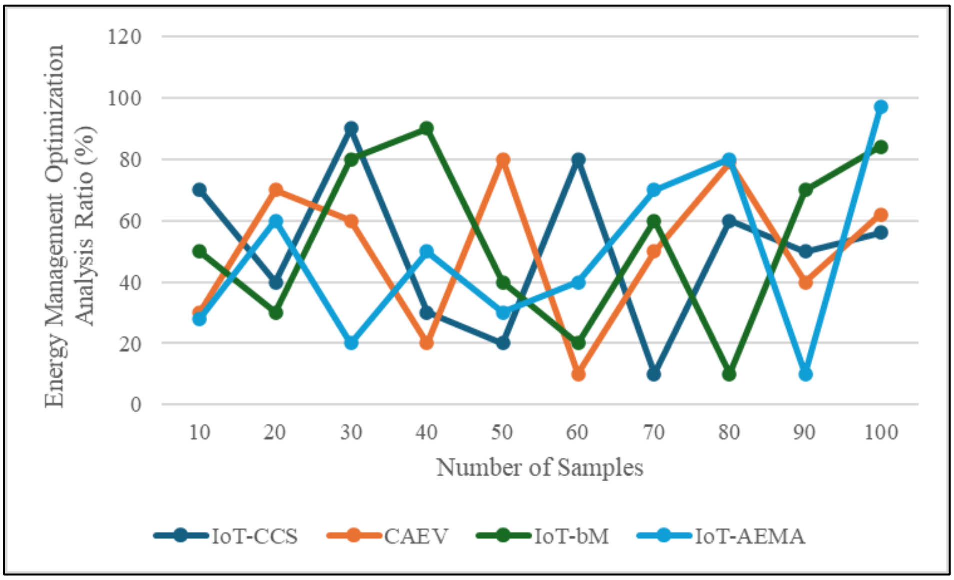

Figure 5. Energy Management Optimization Analysis.

Dataset description

Between November 2014 and October 2015, a group headed by professor of public policy Omar Asensio recorded 3,395 instances of electric vehicle charging using a field experiment [20]. Details such as total energy consumed, cost, date and duration of each session, and 85 EV drivers with recurrent use at 105 stations across 25 locations at a workplace charging program are included in the dataset.

In Figure 5 above, real-time data monitoring and advanced analytics enhance performance and efficiency in Energy Management Optimisation Analysis, as Equation (4) explains. This research focused on EV-IoT integration. This approach uses internet-connected sensors and other technology to track energy usage, battery health, and vehicle performance. Data analysis can improve energy distribution, waste reduction, and battery life. This research allows vehicles to adapt their power consumption to driving circumstances and manoeuvres. Results enable adaptive energy management systems. Enabling energy management with IoT improves predictive maintenance by detecting issues early. Both downtime and maintenance costs drop. Integration with charging infrastructure and smart grids

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ensures energy reliability and grid stability. Using smart grids ensures this produces 97.6%. This increases EV performance and reliability and creates a smart, sustainable mobility environment. The goal of smart city programs is intelligent and eco-friendly transportation.

as explained in Equation (5). Data accuracy helps users, vehicles, and third-party systems like charging stations and traffic control networks connect seamlessly, producing 90.2%. This maintains a healthy and functional commodity and service transfer ecology. EVs with IoT technology provide drivers and manufacturers with more data for decision-making, enhancing dependability, efficiency and connectivity.

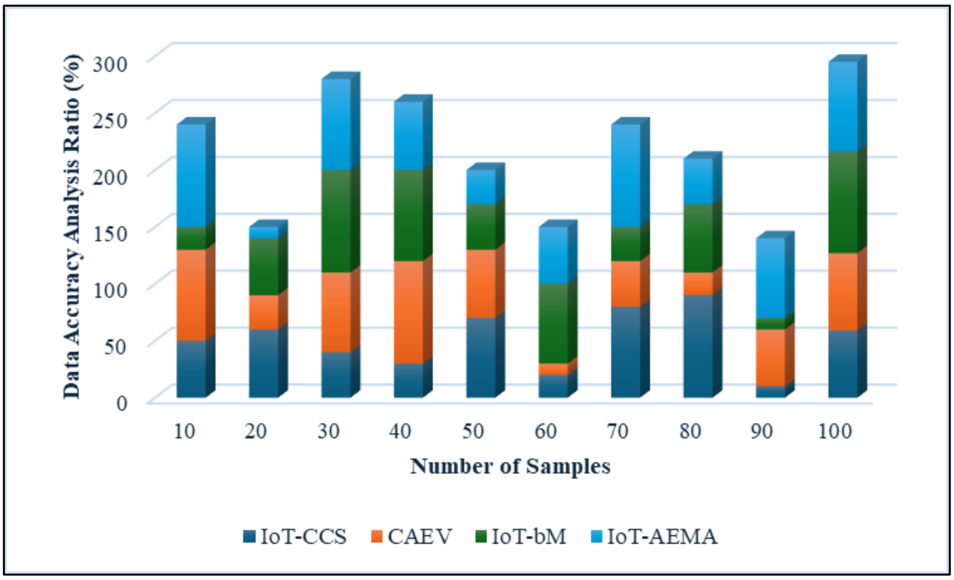

Figure 6. Data Accuracy Analysis.

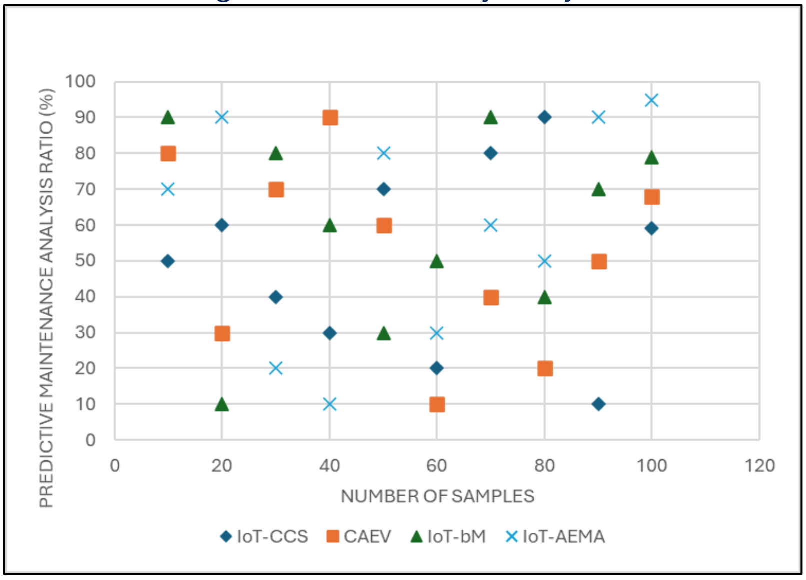

Figure 7. Predictive Maintenance Analysis.

EV performance improved when IoT technology was applied, which demands reliable data processing. Data gathering and processing enable precise vehicle monitoring of battery life, energy usage, and system health. All IoT sensors and devices must communicate data with high data integrity. In Figure 6 above, inconsistencies that could cause danger or poor performance must be eliminated. Building effective data validation and error correction mechanisms helps ensure integrity and reliability. Advanced algorithms and machine learning models analyze this data to provide actionable insights. Results include better energy management and predictive data accuracy maintenance,

Integrating IoT technology into EVs is vital for predictive maintenance analysis, as Equation (6) explains. Continuous monitoring of vehicle components and systems throughout operation is achieved through IoT sensors. Figure 7 above uses this data to assess real-time wear and tear, usage patterns, and potential problems. The data is processed by advanced analytics and machine learning models, allowing for the prediction of when maintenance is needed. Reduced downtime, longer component life, and less chance of unexpected problems are all benefits of this preventative method. In addition to

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ensuring that necessary parts and resources are available, predictive maintenance also helps optimize maintenance schedules and inventory management. Connectivity to the IoT additionally paves the way for remote diagnostics, which can shed light on issues without physically inspecting them, producing 95.7%. Using IoT for predictive maintenance has several benefits, including making EVs more reliable, safer, and efficient, improving the user experience in terms of cost and effort, and laying the groundwork for smarter, more connected transportation systems.

compatibility because numerous sensors, software platforms, and network interfaces exist. Because of this, data exchange and integration will be facilitated, leading to trouble-free system operation. Achieving this objective will need standardization across manufacturer-specific protocols, data formats, and technologies, which produces 93.4%.

Research on potential incompatibilities between EVs and other systems covers their integration with smart grids, charging infrastructure, and traffic management networks. Therefore, to achieve this integration, it is necessary to introduce defined communication protocols. Successful energy management, precise real-time monitoring, and enhanced predictive maintenance depend on fixing these compatibility problems. In addition, it ensures everything is interdependent, improving the user experience and reducing the likelihood of system failures. Thoroughly analyzing system compatibility helps build an electric vehicle ecosystem that is more reliable,

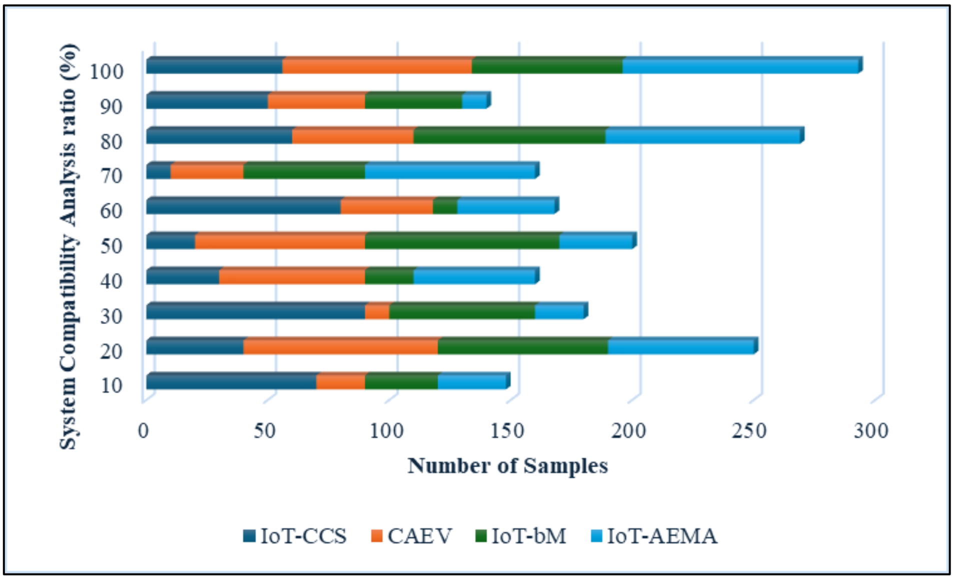

Figure 8. System Compatibility Analysis.

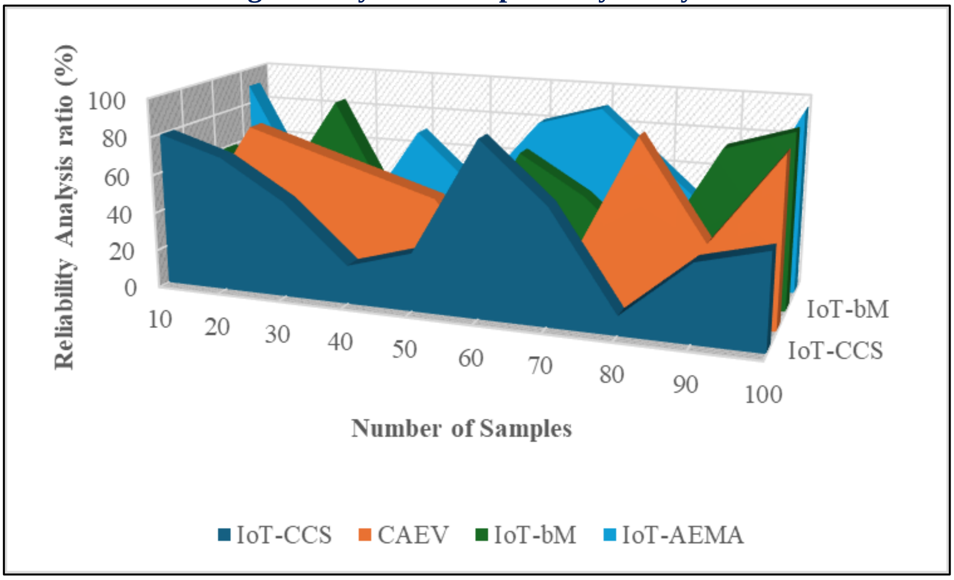

Figure 9. Reliability Analysis.

When introducing IoT technology into EVs, it is necessary to carry out a System Compatibility Analysis, which is explained in Equation (6). This is done to guarantee that the operation operates without problems and that the performance is improved. A wide variety of communication protocols and devices are linked to the IoT. Hence, robust frameworks for standardization and interoperability are necessary. %Figure 8 ensures their efficient, and networked through improved connectivity. This helps get smart transport and eco-friendly city mobility closer to their objectives.

Reliability analysis is essential to these cutting-edge systems, as explained in Equation (7). The IoT for electric vehicles enables predictive maintenance, energy management, and real-time data monitoring. In Figure 9 above, these upgrades boost vehicle performance and driver satisfaction. Analysing IoT component dependability can help manufacturers identify failure sites and improve system design. Thus, the product will be more durable and safe. Strong connectivity from the IoT ensures two-way communication between the car and external networks. This allows enhanced navigation, over-the-air upgrades, and remote diagnostics to be integrated. Electric vehicles' smooth connection adds convenience and innovative features while increasing lifespan. These advantages contribute to the rising popularity of electric automobiles, producing 98.4%. Because of this, a comprehensive reliability study is necessary for EVs to benefit fully from the IoT. Therefore, this will guarantee both the product's performance over time and the customer's satisfaction.

The IoT-AEMA is nearly unanimously acknowledged as the most effective method compared to other methods. It outperforms competing options in terms of performance, reliability, and cost-effectiveness. Table 1 shows the abbreviations.

Table 1. Abbreviations.

Acronyms	Abbreviations
IoT	Internet of Things
EVs	Electric Vehicles
IoT-AEMA	Internet of Things-based Accurate Estimation Monitoring Analysis
IoT-CCS	IoT-based Centralized Control Strategy
PV	Photovoltaic Panel
SEPIC	Single-Ended Primary Inductor Converter
TOPSIS	Technique for order performance by similarity to ideal solution
MPPT	Maximum Power Point Tracking
BMS	Battery Management System
CAEVs	Connected and Autonomous Electric Vehicles
PEV	Plug-in Electric Vehicle

Conclusion

Integrating IoT technology into EVs is a huge leap forward in usability, connectivity, and performance. EVs are becoming progressively growing in popularity. For major issues, including communication network dependability, system interoperability, and data security, a method called IoT-AEMA has been proposed. With IoT-AEMA, various vehicle attributes may be precisely tracked in real time and analyzed in detail. A combination of better energy management, enhanced safety, and the ability to perform predictive maintenance on a predictive basis achieves this goal. Electric vehicles have become more efficient, and their battery life has been extended because this reinforces the interaction between users, vehicles, and external systems like charging infrastructure and traffic management. By conducting simulation experiments in various settings, the practicality of IoT-AEMA has been proven, highlighting its ability to revolutionize engine production. This study's results show that reliable data is crucial for advancing intelligent transportation networks. The improvement of drivers' and manufacturers' decision-making abilities is where this becomes pertinent. A completely linked and optimized transport ecology is starting to sound increasingly like a realistic possibility as EVs keep becoming increasingly successful at integrating into smart city infrastructure and positively impacting pollution levels. An alliance between the IoT and the Automotive Electronics Association has been formed to provide the groundwork for electric vehicles to become an integral part of urban regions' sustainable transportation systems in the future. Another factor that has contributed to preparing for this future is the implementation of better energy management technologies. The arguments presented in this paper favour a team effort, which promotes the growth of an ecosystem where different groups work together to maximize the potential of the IoT in EVs. A more reliable, efficient, and integrated transportation landscape is expected to emerge from this research, which ultimately shows how the IoT has been disruptive to the manufacturing of electric vehicles. The proposed method increases the Energy Management Optimization ratio by 97.6%, Data Accuracy ratio by 90.2%, Predictive Maintenance ratio by 95.7%, System Compatibility ratio by 93.4%, and Reliability Analysis ratio by 98.4% compared to other existing methods. Using the most advanced machine learning techniques for predictive analytics can improve the accuracy of battery life and energy consumption forecasts. Improvements to scalability can be achieved by connecting the system with a more diversified smart grid infrastructure and broadening its support for a wider variety of electric vehicle types. Optimal energy distribution via real-time V2G communication is another area that will be investigated in future studies. Essential areas of investigation will include testing the system in real-world conditions and measuring its influence on EV performance and user experience.

Conflict of Interest

The authors declare that there is no conflict of interest.

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