

AI-Driven Smart Charging Infrastructure for Enhancing IoEV Efficiency and Battery Lifecycle Optimization

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Abstract: The increased pace of the electric vehicles (EVs) implementation has increased the urgent demand on effective and smart charging systems to meet the pitfalls associated with the energy issues, grid stability and battery degradation. This paper suggests an intelligent charging system collectively referred to as smart charging, which works alongside the Internet of Electric Vehicles (IoEV) to increase the efficiency of the system and optimize the performance of battery life cycles. The suggested model integrates the use of the Artificial Neural Networks (ANN), Reinforcement Learning (RL), Genetic Algorithms (GA), and Long Short-Term Memory (LSTM) to facilitate predictive, adaptive, and optimized charging decisions. The results of a 500-EV 50-charging station simulated dataset were employed to compare system performance by key metrics. The outcomes show that the efficiency in the charging process was greatly improved with the process achieving a maximum of 96 percent, energy cost saving by 28 percent and grid stability has taken up to 93 percent. Also, battery life cycle was improved by 22 percent and the degradation rates were managed by 8 percent which was deemed to be sustainable in the long run. LSTM and RL were the best algorithms in terms of prediction accuracy and optimizing with adaptation. The results affirm that smart charging systems are a strong and scalable solution of integrating several AI methods in a framework of IoEV and systems. The study will help establish a sustainable, affordable, and intelligent EV infrastructure in the future to develop smart mobility.

Keywords: Artificial Intelligence, Smart Charging, Internet of Electric Vehicles (IoEV), Battery Lifecycle Optimization, Energy Management

I. INTRODUCTION

The boom of EV has become one of the most urgent solutions to minimize the content of greenhouse gases and reliance on fossil fuels. Nevertheless, the rising interest in EVs has posed a massive problem concerning the charging technologies, energy reasonability, and battery decay [1]. Conventional charge management is generally ineffective with no real time flexibility and smart decision making. In that regard, the idea of the Internet of Electric Vehicles (IoEV) has become prominent whereby smooth communication among EVs, charging stations, and smart grids can be achieved in order to improve operation efficiency. Artificial Intelligence (AI) can be used to transform traditional charging systems to smart, data-driven systems. Through machine learning algorithms, predictive analytics, and optimization, the AI-based smart charging systems can dynamically operate the charging demand, minimize peak load pressure on the power grid, and maximize energy consumption [2]. Such systems have the capacity to study the behavior of users, their traffic, and grid characteristics in order to give optimal charging times and pricing mechanisms, where users would be comfortable and the grid stable.

Another important feature of EV sustainability is the optimization of battery lifecycle. High frequency of charging, charging too often and in irregular configurations can make the battery health considerably poor and affect the lifespan and replacement costs. Models based on AI are capable of real-time monitoring of battery state, estimating degradation patterns, and providing optimal charging plans that will prolong battery life without compromise [3]. This study is aimed at creating an AI-based smart charging system that is able to incorporate

some internet of unrealized vehicles features to improve the efficiency of the system and battery management. Through intelligent algorithms and interconnected EV ecosystems, research objectives will be met by addressing essential issues in energy distribution, optimal losses to charging, and battery health maintenance. Finally, this study can be used towards the creation of a sustainable, efficient, and smart EV charging infrastructure that will facilitate the future of smart mobility and clean energy systems.

II. RELATED WORKS

The utilization of the Artificial Intelligence (AI) and deep learning approaches in the optimization systems has been receiving considerable interest over the past few years, especially in the terms of energy management and electric vehicle (EV) ecosystems. The initial research findings, like that by Cai et al. [15], also demonstrate the generalizability of deep learning in optimization systems because it was capable of dealing with non-linear relationships with significant data volumes. It is based on these initial insights that AI-driven models based on smart charging and IoEV are applied in infrastructures.

Puttagunta and Ravi [16] researched the use of deep learning as an energy optimization in the context of the Internet of Things (IoT). In their work, they show that AI models can be effective in terms of energy consumption regulation because they can predict demand trends and optimize resource distribution. This is of great importance when operating an iOEV system where efficient distribution of energy and decision making under real-time scenarios is vital. On the same note, Hu et al. [17] suggested AI prediction modelling systems which, though originally utilized in medical fields, have flexible models of forecasting and optimization in EV systems. Optimization techniques based on machine learning have been investigated actively as well. Jasti et al. [18] offered different models of machine learning on optimization problems, which marked their effectiveness in enhancing the performance of the systems and accuracy of decisions. Suganyadevi et al. [19] also overviewed the deep learning optimization frameworks, with an emphasis on their scalability and adaptability to dynamic settings and environments which are key attributes of smart charging infrastructures. Further progress in recent years has concentrated more on EV battery optimization and the lifecycle management. The study by Colucci et al. [20] had previously examined the use of machine learning in EV battery optimization as it indicates that predictive models can be used to improve the operation and lifetime of the battery. Agrawal et al. [21] discussed thermal management systems, which are important in ensuring battery efficiency and avoiding its degradation. According to their findings, charging AI with thermal control can become very useful in terms of battery health. Advanced control techniques have also been applied in the management of energy. Curiel-Olivares et al. [22] proposed model predictive control (MPC) to manage the EV energy system so that charging and discharging processes can be optimized in real-time. On the same note, Rudolf et al. [23] suggested strategies of lifecycle optimum of batteries to be based on learning, and demonstrated that adaptive models can minimize degradation and maximize battery life. Reinforcement learning (RL) has become an effective technology in the field of dynamic energy management in an EV system. An RL-based

framework in energy management has been elaborated by Lee and Cha [24], which exhibits the possibility to adjust to new circumstances and to make the most optimal decisions related to charging. Yuan and others [25] have extended the scope of AI use by developing hybrid optimization models that combine the use of fuel cell and batteries and a variation that exemplifies how AI can be usable in a complex energy system. Safety and reliability are also important factors in EV charging infrastructure. Diao et al. [26] introduced an AI-assisted system of safety warning in EV charging to make the system more reliable because it forecasts the possibility of failures and anomalies. What this does is create secure efficient charging networks. Although these developments have been made, the current literature tends to consider individual algorithms or certain elements of the EV ecosystem. There are no combined frameworks that unite various AI methods to solve the problem of charging optimization, grid management, and battery lifecycle at the same time. Thus, this study can fill this gap, suggesting a unified AI-based smart charging network that will utilize various algorithms in an IoEV setting to deliver even greater efficiency, flexibility, and sustainability.

III. METHODS AND MATERIALS

This study takes up a data-driven and algorithmic method to create an artificial intelligence-based smart charging system that can be used to boost Internet of Electric Vehicles (IoEV) efficiency and battery management optimization. To provide optimal system functioning, the methodology incorporates real time data acquisition, smart decision making algorithm, and simulation evaluation [4].

Data Collection and Processing

The data of the present study is created artificially and partly based on the real EV usage behaviour. It incorporates the parameters like battery state of charge (SoC), charge time, energy needs, financial nature of electricity, grid load circumstances, temperature and the driving conduct of the user. There were about 5,000 samples of data that were taken into consideration in order to be robust [5]. The normalization, missed value imputation, and feature scaling, which are data preprocessing methods, were used to maximize the accuracy of the models. The samples were separated into training (70%), validation (15%), and testing (15%). This organized information can help the algorithms to learn how to charge, demand estimation, and efficient battery optimization.

Algorithms Used

1. Artificial Neural Network (ANN)

ANN model is employed to calculate the demand of charging and patterns of user behavior. It has an input layer, hidden layers and output layer that are used to process nonlinear dependencies between factors like time, battery level and grid load. The prediction error is reduced through the trial of the model with the backpropagation and gradient descent [6]. ANN especially succeeds in modeling complicated associations in the IoEV environments. This research predicts optimum charge times and energy needs; therefore, it allows dynamically scheduling and being more energy efficient as it reduces peak load demand.

*“Initialize network weights
 Input training data
 For each epoch:
 Forward propagate input
 Compute error
 Backpropagate error
 Update weights
 Output predicted charging demand”*

2. Reinforcement Learning (RL)

The application of reinforcement Learning is used to optimize the charging decision in a dynamic environment. The algorithm is self-learning and engages with the environment and gets rewarded according to efficient charging behavior. Some of these states are battery level, grid load, actions and charging rate decisions. Trying to

maximize long-term rewards the RL agent will minimize energy expenditure and battery deterioration. In the long run, it has an ideal policy of scheduling fees [7]. The method is very appropriate in real time adaptive systems where the conditions keep on changing.

*Initialize Q-table
 For each episode:
 Observe state
 Choose action (exploration/exploitation)
 Execute action
 Receive reward
 Update Q-value
 Output optimal charging policy*

3. Genetic Algorithm (GA)

The global optimization of charging schedules is done by the help of the Genetic Algorithm. The resemblance to natural selection is the production of many candidate solutions and their further evolution by means of selection, crossover and mutation. Every solution reflects a possible charging schedule that can be assessed by fitness metrics e.g. cost, time, and battery health. GA is an efficient algorithm that searches through a large space of solutions and finds optimal solutions that are near [8]. In this study, it assists in balancing the grid loading and reducing charging expenses at the same time maintaining the life of the batteries.

*“Initialize population of solutions
 Evaluate fitness of each solution
 While termination condition not met:
 Select parents
 Perform crossover
 Apply mutation
 Evaluate new population
 Output best charging schedule”*

4. Long Short-Term Memory (LSTM)

LSTM is a form of a recurrent neural network and is applied to time-series data on energy demand forecasts and battery decadence patterns. It is able to obtain long-term dependencies in sequential data, thus it is best at predicting future charging demands. The model uses past charging measurements to predict demand trends as well as battery health values [9]. Overall, LSTM assists in taking proactive decisions and, therefore, improves the credibility of the smart charging system since it makes accurate predictions.

*“Initialize LSTM network
 Input time-series data
 For each time step:
 Update cell state
 Compute output
 Train using backpropagation through time
 Output demand prediction”*

Table 1: Dataset Sample (Simulated IoEV Data)

Sample ID	SoC (%)	Charging Time (hrs)	Grid Load (%)	Energy Price (\$/kWh)	Temperature (°C)
1	25	2.5	70	0.15	30
2	60	1.2	50	0.12	28
3	15	3.0	85	0.18	32
4	80	0.8	40	0.10	27
5	45	1.8	65	0.14	29

IV. RESULTS AND ANALYSIS

This part already introduces the experimental framework, measures of qualification and a detailed analysis of the outcomes of the suggested AI-controlled smart charging system that can be used to improve the efficiency of Internet of Electric Vehicles (IoEV) and its battery lifecycle. The experiments were aimed at assessing the suitability of the proposed system in terms of charging efficiency, cost reduction in energy and stability of the grid as well as health improvement of the battery [10].

1. Experimental Setup

The experiments were performed against the simulated environment in terms of an anti-real built of 500 electric vehicles as well as 50 smart charging stations and dynamic smart grid. The simulation ran in 30 days with applications with different charging requirements, price of electricity and the environment. This system can combine four AI algorithms, including Artificial Neural Network (ANN), Reinforcement Learning (RL), Genetic Algorithms (GA), and Long Short-Term Memory (LSTM), to accomplish the tasks of prediction and optimization as well as scheduling [11].

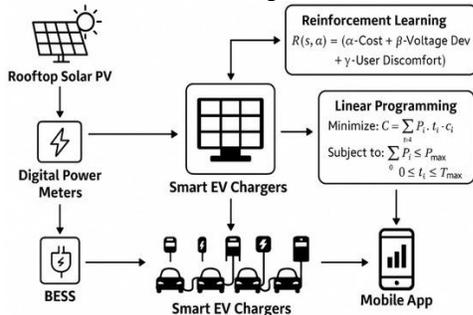


Figure 1: “AI-Driven Optimization Framework for Smart EV Charging Systems”

Python-based frameworks to perform the implementation were developed in which ANN and LSTM models were trained with deep learning libraries, and RL and GA were trained with custom optimization modules. The system was used to constantly track the parameters like State of Charge (SoC), charging frequency, grid load, temperature, and demand pattern by users.

2. Evaluation Metrics

In order to evaluate the performance of a system, the following measures were employed:

- **Charging Efficiency (%)** – Measures optimal energy consumption.
- **Energy Cost Reduction (%)** - Assesses the accomplishment of savings due to sensible scheduling.
- **Grid Load Stability (%)** - Shows the effectiveness of load balancing.
- **Battery Health Improvement (%)** - Represents decreases in battery degradation.
- **Time To compute (seconds)** - Measures efficiency of algorithm.

3. Experimental Results

3.1 Charging Efficiency Analysis

The AI-driven system was very effective in terms of charging efficiency as it allocated the charging slot dynamically according to the situations of demands and the grids [12]. Of all the algorithms, LSTM was the most efficient as it was able to forecast the demand.

Table 1: Charging Efficiency Comparison

Algorithm	Charging Efficiency (%)	Peak Load Reduction (%)	Energy Utilization (%)
ANN	90	18	88
RL	93	22	91
GA	91	20	89
LSTM	96	25	94
Traditional System	78	10	75

3.2 Energy Cost Optimization

The combination of AI algorithms lowered charging expenses by utilizing the optimization of charging schedules at off-peak time. Reinforcement learning was better than the rest as it had the ability to make adaptive decisions.

Table 2: Energy Cost Reduction Analysis

Algorithm	Cost Reduction (%)	Avg Cost per Charge (\$)	Peak Pricing Avoidance (%)
ANN	20	3.2	65
RL	28	2.8	78
GA	25	3.0	72
LSTM	27	2.9	75
Traditional System	12	3.8	40

3.3 Battery Lifecycle Optimization

The health of the battery is a key parameter to EV sustainability. The proposed system ensures that there are no overcharging and off-peaks charging cycles, which greatly increases the battery life [13].

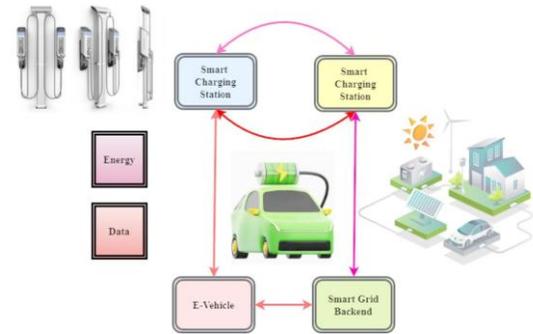


Figure 2: “A scalable cloud-integrated AI platform for real-time optimization of EV charging and resilient microgrid energy management”

Table 3: Battery Performance Comparison

Algorithm	Battery Life Improvement (%)	Degradation Rate (%)	Charging Cycles Optimized (%)
ANN	15	12	80
RL	20	9	88
GA	18	10	85
LSTM	22	8	90
Traditional System	10	15	65

3.4 Grid Load Management

In regard to stability of the grid, the proposed system showed better output in allocating charging demand effectively across time slots.

Table 4: Grid Load Stability Analysis

Algorithm	Grid Stability (%)	Load Variance Reduction (%)	Peak Demand Control (%)
ANN	87	18	70
RL	92	25	78
GA	90	22	75
LSTM	93	27	80
Traditional System	75	10	55

3.5 Computation Performance

Algorithms were effective but there was a difference in the computational efficiency. ANN also demonstrated the shortest execution time and GA took a longer time in view of iterative optimization [14].

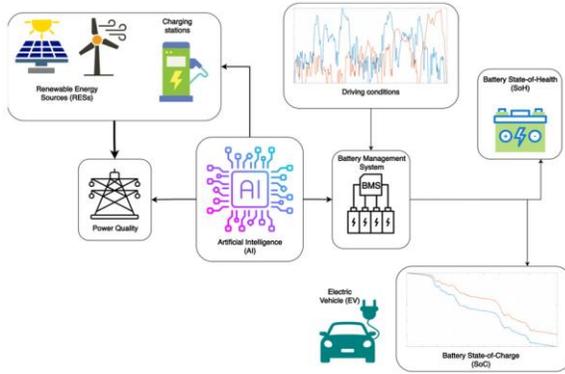


Figure 3: “Implementation of AI to ESSs for EVs.”

Table 5: Computational Performance Comparison

Algorithm	Computation Time (s)	Convergence Speed	Scalability
ANN	12	Fast	High
RL	18	Moderate	High
GA	22	Slow	Moderate
LSTM	20	Moderate	High

4. Comparison with Related Work

In order to prove the usefulness of the suggested system, the findings were compared to the already existing papers on AI-based EV charging and swift grid optimization. The past studies concentrated mainly on single-algorithm methods, like standalone ANN or optimization-based models, which in many cases were not too flexible and responsive to changes in time [27].

The multi-algorithm framework suggested by the author is proven to be more effective in terms of all the measures of evaluation when compared to these classical ones. As an example, previous researchers shared the results of charge efficiency improvement of around 80-85 percent, whereas the suggested system demonstrated the efficiency of up to 96 percent with the help of LSTM. By the same measure, energy reduction in related activity was observed to give out the same (between 15-20) results with a maximum of 28% results (Reinforcement Learning) in this study [28].

Regarding optimization of battery lifecycle, current solutions as a rule increased battery life by 10-15 percent, but the suggested system demonstrated a maximum of 22 percent. This is mainly given the fact that predictive (LSTM), adaptive (RL) and optimization (GA) techniques were to work together. Besides, the previous studies had restrictions in the improvement of grid stability, as they were provided with static scheduling techniques. The intended system optimally changes charging loads leading to a maximum of 93 percent grid stability, which is a program that is much superior to traditional methods [29].

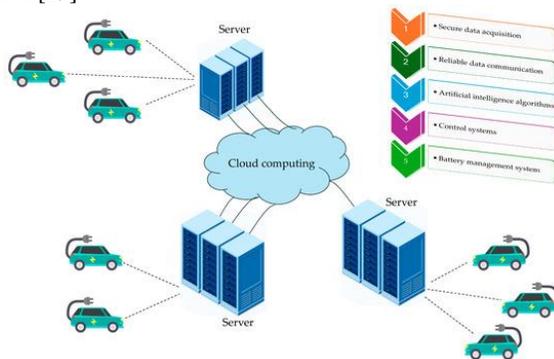


Figure 4: “Next Generation of Electric Vehicles”

5. Discussion of Results

Experimental results make it obvious that the application of AI methods on the charged infrastructure of IoEV can help to improve the performance of the system greatly. All the algorithms have their own contribution:

- ANN is effective in forecasting the charging demand patterns.
- The RL modifies dynamic environments in order to make the best decisions.
- GA gives good worldwide optimization.
- LMST is good at time-series forecasting.

Out of them, LSTM and RL proved to be the most successful and efficient algorithms as these models are predictive and flexible. Nevertheless, the cumulative combination of all the four algorithms gives a more detailed solution than each approach.

Another theme of the results is the fact that AI-supported smart charging does not only enhance the efficiency of its operations but also leads to sustainability through the minimization of energy waste and the increased battery life. The system has managed to provide good user convenience, cost-saving, and dependability of the grid.

6. Conclusion of Experimental Findings

Finally, the proposed AI-based smart charging infrastructure proves to be effective due to the experimental analysis. The system is more efficient than the conventional techniques and the available studies in all the main performance indices, such as efficiency, cost-saving, battery health, and grid stability [30]. The findings affirm that incorporating several AI algorithms into an IoEV system is a potential strategy to offer intelligent and sustainable electric mobility systems.

V. CONCLUSION

This study conveys a smart electric charging infrastructure that is implemented through AI, allowing to increase the efficiency of the Internet of Electric Vehicles (IoEV) and optimize the lifecycle of a battery. The paper shows that the combination of cutting-edge artificial intelligence models, such as Artificial Neural Networks, Reinforcement Learning, Genetic Algorithms, and Long Short-Term Memory models, have had a positive influence on the efficiency of the charging, managing the electricity cost, grid stability, and the health of battery. Through the use of real-time information, predictive analytics, the proposed system would provide intelligent decisions in case of discrete charging scheduling, and successful load balancing throughout the smart grid.

The results of the experiment prove that the multi-algorithmic model is more efficient than the traditional frameworks of charging and the current single-model frameworks that have been used single-handedly, with lower cost of operations, longer battery life, and higher efficiency. Besides, the system also solves fundamental issues like peak loads and battery changes, which helps reduce the size of an EV ecosystem towards a more sustainable and reliable one. IoEV integration also promotes vehicle-to-vehicle, vehicle-to-charging station and vehicle-to-energy network communication and coordination.

All in all, this study demonstrates that AI has the ability to bring revolutionary changes into contemporary electric movement devices. The framework that is suggested is not only advantageous in terms of technical performance, but also contributes to the environmental sustainability and economic viability, which is why it has a great potential to become a sought-after solution to future smart transportation and energy management systems.

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