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Research Article

Smart Charging Solutions for Electric Vehicles: An AI-Driven Approach to Load Balancing and Grid Integration

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ABSTRACT

Today, the integration of Electric Vehicles (EVs) into the grid is a critical issue with inefficiencies in real-time demand management, scalability, as well as security threats to centralized infrastructure. The fast increase in EV adoption poses several challenges including grid overloading and energy distribution wastage. Thus, there is a need for an intelligent, scalable, and secure charging solution to avert disruption as well as improve energy efficiency that will ensure the sustainable growth of electric mobility. The study emphasizes on development of an AI-driven platform using demand response and load-balancing techniques for EV charging. Including predictive analytics based on AI technology, the system enhances grid stability in addition to optimizing energy consumption. To resolve the challenges, the paper presents load balancing with an Artificial Intelligence (AI) system employing AI-driven predictive demand forecasting. Dynamic load balancing optimizes EV charging infrastructure. The system proposed in this study enhances the stability of the grid, with a 20% decrease in peak-period overload, as well as a cost reduction of 20.38%. These results offer efficient and sustainable EV charging infrastructure facilitating the broader deployment of electric mobility.

Keywords: Electric Vehicles, Smart Charging, Load Balancing, Artificial Intelligence, Power Grid.

INTRODUCTION

The shift to sustainable transport is vibrant in addressing environmental as well as energy issues. Electric vehicles (EVs) replacing internal combustion engine (ICE) vehicles, help reduce greenhouse gas emissions as well as effectively decrease air pollutants [1]. However, the green credentials of EVs, rely on the power generation mix [2]. EVs powered by electricity from fossil fuels make a contribution to decarbonization is diminished. Thus, smart charging solutions are desirable to exploit energy usage besides tapping renewable sources of energy to their maximum capacity. Smart charging solutions for electric vehicles utilize sophisticated technologies to manage charging behavior, reduce grid load, and enhance energy efficiency overall. Intelligent charging is more efficient than conventional charging as it allows dynamic scheduling according to real-time grid conditions, electricity prices, and the availability of renewable energy. It incorporates grid-to-vehicle (G2V) as well as vehicle-to-grid (V2G) capabilities so EVs can be used as energy storage devices that feed power back to the grid during peak hours [3]. This not only stabilizes the grid but also makes EVs a component of the energy system to enable smart grids, microgrids, and virtual power plants.

In EV grid integration, load balancing [4] is an important method, distributing the charging load uniformly across the grid to avoid voltage instability, power loss, and supply inadequacy. Uncontrolled EV charging can lead to grid imbalances, voltage fluctuations, and other harmonic distortions, compromising power quality. Through AI-based load balancing [5], charging stations can reoptimize power allocation in real time as per accessible energy, grid conditions, and demand projections. Techniques like deep learning and machine learning are used to charge artificially with maximum efficiency by forecasting usage patterns and re-mapping loads accordingly. Smart grid integration is made central by AI-based solutions through predictive demand management, real-time load allocation, and fault detection. Machine learning algorithms [6] scan past records to predict peak demand periods, and deep learning algorithms increase the robustness of grids by dynamically adjusting charging rates. Reinforcement learning also supports adaptive energy management through the effective distribution of energy without grid congestion. Blockchain technology [7] also ensures security and transparency by enabling decentralized energy trading and creating trust among participants. By implementing AI-based smart charging and load balancing, EV infrastructure can become more efficient, scalable, and sustainable. These technologies minimize power fluctuation, stabilize the grid, and optimize the use of renewable energy sources, which essentially translates to a greener and stronger energy future.

The integration of renewable energy sources (RESs) into electric vehicle (EV) charging stations [8] offers a revolutionary opportunity to curb carbon emissions and improve grid stability. Nevertheless, the uncertainty associated with renewable energy generation poses important challenges to securing a stable and efficient supply of energy. Artificial Intelligence (AI) is responsible for bridging the gap over such challenges by providing predictive analytics, real-time optimization [9], and autonomous decision-making for smart grid systems. AI-based smart grids adjust energy distribution dynamically, balance demand and supply, and optimize load-balancing policies to make grid operation a breeze. Predictive analysis of renewable energy availability is one of the most important applications of AI in smart grids. AI programs study past and current weather trends to predict energy production from RESs so that EV charging stations can plan the charging process during periods of excess renewable energy production. This way, EVs are charged with green energy, ensuring maximum sustainability and minimizing the use of fossil fuel-based power generation. Through synchronization of the charging schedule with renewable energy, AI systems make the energy system greener and more sustainable.

The smart grid AI is smart grid integration, which involves the use of AI-based algorithms to optimize coordination among EVs, renewable energy sources, and energy storage systems [10]. Using real-time data processing and predictive analysis, AI optimally distributes energy resources, avoiding overload and maximizing grid effectiveness. The heart of this is vehicle-to-grid (V2G) technology, which allows bidirectional energy transfer where EVs can supply extra energy back to the grid when there is peak demand [11]. This not only stabilizes the grid but also offers economic incentives to EV owners who engage in energy trading markets. AI further enables energy arbitrage and load balancing, in which charging stations can pull in excess renewable energy during low-demand hours and dispatch it during peak-demand hours. This action prevents grid congestion [12], averts voltage instability, and maximizes the economic feasibility of charging devices by cutting down on the cost of energy. Machine learning algorithms continuously monitor patterns of energy usage and dynamically modify charging rates to provide optimal grid balance. Through this, AI-powered energy arbitrage provides a sustainable and cost-effective method of EV charging.

For off-grid or remote locations, AI enables off-grid renewable charging systems [13] through the control of microgrid systems based on locally available renewable energy. AI programs track the level of energy storage, forecast energy usage patterns, and control power distribution in real time. These systems enable seamless EV charging by maintaining energy supply and demand equilibrium within localized networks. With the use of AI-based microgrids, EV charging stations [4] can be extended to remote areas with poor access to centralized power grids, enhancing energy independence and sustainability. In summary, artificial intelligence-driven smart grid technology is at the center of the transformation of EV charging infrastructure through increased grid reliability, maximized energy utilization, and the smooth integration of renewables. AI [6] raises the efficiency and sustainability of smart grids to a more cleaner and reliable transport system through predictive analytics, load balancing, and intelligent energy management.

The study of AI-driven smart charging technology for EVs is intended to prioritize load balancing and grid integration to increase energy efficiency as well as stabilize the grid. The study involves predictive demand forecasting, dynamic load allocation, and decentralized energy management using AI technologies. The significance lies in addressing the grid congestion, peak load stress, and energy inefficiencies towards the culmination of an end to a more scalable and robust EV charging infrastructure. It is a part of conceptualizing the demand response load balancing and grid integration using AI framework, whereby the EV charging activity is optimized but with the assurance of secure and tamper-proof energy transactions. The objectives are to enable real-time grid flexibility, reduce peak demand stress, improve data security, and increase the use of renewable energy. Through real-time decision-making using AI and V2G operation, this study aims to contribute to the sustainable growth of EV penetration without compromising the stability of the grid.

LITERATURE SURVEY

Emerging research covers the increasing role of AI, IoT, and digitalization in transforming EV charging infrastructure in the smart grid context. Demand planning, dynamic load management, and integration of renewable energy and AI-based predictive analysis have been examined to boost the efficiency of the grid. Increasing applications of V2G and G2V technologies [14] have also emerged as focal points for smart energy management. Research also examines secure energy transactions with more open, and decentralized grid operation. With the growing proportion of distributed energy resources (DERs) and energy storage systems [15], AI-based optimization techniques are proving to be essential for ensuring grid stability, sustainability, and economic efficiency.

In real-time monitoring, the integration of Artificial Intelligence (AI) [6] into smart grids has revolutionized the management of electric vehicle (EV) charging stations by allowing prediction, as well as self-adjusting load balancing. Bouquet et al. [16] achieved efficient delivery of electricity with AI-powered smart grids maximizing the power grid distribution and minimizing disruptions irrespective of fluctuating demands. Traditional grid infrastructures induced voltage instability, energy loss, and peak load tension, which are reduced by AI-based solutions via dynamic energy reorganization, demand prediction, with real-time grid operation adjustment. In AI smart grids, advanced load balancing is one of the distinguishing contributors. Mohseni et al. [12] show that conventional power distribution networks tend to be based on static configurations that are unable to handle the increasing number of EVs. AI models, especially ML, and deep learning, evaluate past and current data to forecast demand fluctuations while automatically allocating power between substations. According to research studies, MIQCQP and MILP models have proven to be effective, in optimizing grid performance, power losses, and reliability.

Besides, Grid-to-Vehicle (G2V) and Vehicle-to-Grid (V2G) technologies have also allowed bidirectional energy exchange, which makes it possible for EVs to function as energy storage units that improve the stability of the grid. Intelligent grids controlled dynamically by AI manage these exchanges, maximizing the use of DERs, renewable energy, and microgrid systems [17]. AI also strengthens grid security by integrating blockchain technology, whose application makes transactions in energy decentralized and tamper-proof, removing weaknesses associated with centralized systems. Shetty et al. [18] further investigate AI capabilities in predictive analytics for renewable energy supply, such that EV charging points function well on clean energy. Energy arbitrage through AI enables smart grids to accumulate surplus renewable energy when demand is low and release it when demand is high, cutting operational costs and grid congestion. Through continued advances, AI-based smart grids are poised to increasingly enhance sustainability, scalability, and economic efficiency and thus become necessary for EV integration and energy management in the future.

Shern et al.'s [6] study of EV charging infrastructure in Malaysia emphasizes the groundbreaking role of AI in making charging more efficient and grid robust. Through a study of directions in the market using Total Industry Volume (TIV) and Total Industry Production (TIP) movements, the research indicates significant breakthroughs in AI-led solutions. ML-based predictive analytics significantly enhanced user experience and enabled optimal energy management. AI-based smart charging model delivered 30% energy savings as well as 20.38% cost savings. It illustrated the capability of AI to advance the economic attractiveness and environmental sustainability of EV charging infrastructure. Moreover, Ahsan et al. [19] evaluate the EV-grid integration function with emphasis on the influences of smart charging technologies on the stability of grids, consumers' behaviors, environmental sustainability, and development of energy infrastructures. The study also demonstrates essential problems in EV-grid dynamics and the essential for AI-based smart charging technologies to maximize energy delivery. The research solves these issues, thereby highlighting the potential of smart charging systems to promote a more sustainable and robust transportation energy system.

In recent years, several studies have been carried out on AI-based smart grids for electric vehicle (EV) integration concerning security, energy management, as well as optimization. The research by Hossain et al. [20], included cooperative spectrum sensing using CR-VANETs (Cognitive Radio Vehicular Ad Hoc Networks) for enhancing spectrum efficiency to facilitate hassle-free communication among EV networks. Furthermore, Singh et al. [7] proposed a DET Framework (Decentralized Electricity Trading) that utilizes blockchain as well as ML to optimize electric V2G electricity trading. It aimed to maximize cost-effectiveness and reliability in decentralized energy trades. In a study [21], Rana et al. presented security as a matter of urgent concern in smart grids. They proposed a protocol for detecting spurious data injection attacks in peer-to-peer (P2P) energy trading as an anti-attack against cyber-attacks in decentralized energy exchanges. Also, Heinekamp et al. [22] researched the role of ICT (Information and Communication Technology) in managing demand, while presenting measures for increasing the efficiency of grids and balancing the load through smart automation. Integration with renewable energies, by Manzolini et al. [23] focused on models of photovoltaic power forecasts for smart microgrids by applying AI-entrenched forecast practices to the enhancement of distributed energy resources' sustainability and credibility. They emphasized the importance of AI with predictive analytics in improving smart grid performance for the integration of EVs. It is the foundation for smart energy management, and renewable energy forecasting that enables the creation of sustainable and resilient power systems.

2.1 Research Gaps

Although much advancement has been achieved, there are some gaps in AI-based smart grids for EV integration. Other studies solve specific areas of spectrum sensing, electricity trading, security, demand-side management, and renewable forecasting but fail to do so under an all-encompassing framework that ties together these considerations for real-time smart EV charging. In addition, current models fail to efficiently address dynamic load balancing in grids with high EV penetration, resulting in power loss and grid instability. While blockchain-based electricity trading has been experimented with, a lot of research is still left on AI-driven predictive analytics' ability to optimize energy arbitrage, power distribution, and charging schedules. Besides, most of the existing research focuses on static grid configurations and does not consider the potential of AI-supported adaptive energy routing based on real-time demand fluctuations.

The AI-based load balancing and grid integration system introduced here overcomes such drawbacks by leveraging predictive analytics, real-time energy distribution, and AI-facilitated demand forecasting to allow maximum optimization of EV charging station operations. Dynamic load balancing is facilitated by machine learning algorithms foretelling demand for charging, grid congestion, and renewable energy supply. AI-facilitated protocols, blockchain-secured, also ensure safe and effective P2P energy transactions. By incorporating V2G (Vehicle-to-Grid) and microgrid optimization, the platform significantly improves grid resilience and energy sustainability for generations of smart EV charging infrastructures to come.

METHODOLOGY

The proposed AI-based demand response and load-balancing system employs predictive demand forecasts and dynamic load balancing to achieve optimal EV charging infrastructure. AI algorithms predict energy demand variations using historical and real-time records of charging patterns, grid load, and renewable energy supply. The system actively controls charging loads according to these forecasts. The system makes adaptive changes in charging schedules and power assignments, minimizing overload during peak hours and avoiding grid congestion. This AI-based strategy includes uniform load balancing to enhance the grid stability considering power between charging points, as well as optimal renewable energy utilization along with enhanced overall efficiency of the EV charging network.

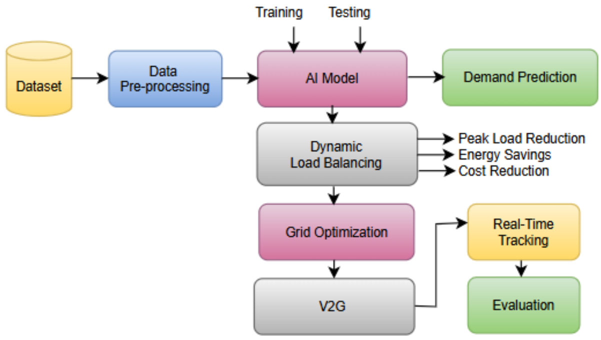

Fig. 1 Block diagram of Proposed AI-based method for Smart EV Charging using Load Balancing

3.1 AI-based Smart EV Charging Model

- **Data Collection:** The study collects EV charging data that consists of real-time as well as historical charging sessions. The data is collected from multiple charging locations including vital parameters such as grid load fluctuations, per-session energy consumption, user demand profiles, charging commencement and completion time, and charging power values. It also captures peak and off-peak periods of charging, renewable energy availability, and dynamic price fluctuations to mimic actual real-world grid scenarios. The dataset trains the artificial intelligence models for predictive demand forecasting and adaptive load balancing, thereby resulting in increased grid stability and efficiency in EV charging systems.
- **Data Preprocessing:** This entails cleaning and converting raw EV charging data into accurate and consistent data before ingesting it into the AI model. It comprises imputing missing values, standardizing the energy consumption as well as charging duration, and removing sensor errors along with outlier-caused anomalies. Feature selection selects prominent characteristics like charging pattern, peak demand hour, as well as grid load fluctuations. The model performance boosts with time-series segmentation and categorical encoding of variables. Preprocessing ensures the AI-driven load-balancing system working optimally with high predictive capability.
- **AI Demand Forecasting Model:** Advanced ML models for time-series prediction, analyzing past patterns of charging, and predicting future energy demand. External factors like weather, traffic volume, and grid capacity are factored in while making accurate predictions of demand. With a pre-eminent prediction of peak demand hours, the system can look ahead and distribute energy resources efficiently, preventing unexpected grid overloads and ensuring smooth functioning.
- **Dynamic Load Balancing and Grid Optimization:** The AI dynamically optimizes the charging schedule and power distribution across different charging stations based on demand predictions. The grid is optimized by maximizing the utilization of renewable energy sources, charging speed variability, and load reallocation to less charged charging stations. Reinforcement learning techniques allow the AI system to learn in real-time and improve the energy distribution strategy in real-time depending on prevailing grid conditions and preventing substation stress.
- **Vehicle-to-Grid (V2G) Integration:** For optimal sustainability, the AI system incorporates renewable energy sources such as solar and wind power into charging EVs. It charges EVs during periods of high renewable energy generation to ensure EVs are filled with clean energy. V2G technology also allows EVs to give excess energy

to the grid when demand is high, serving as decentralized energy storage devices that improve grid stability and efficiency.

- **Real-Time Tracking:** The system runs with continuous real-time monitoring of grid conditions, energy needs, and station use via IoT sensors and cloud systems. Predictions and strategies for load balancing are updated in real time and aligned to include unpredictable fluctuations. Insights are also communicated to the grid operators and the EV drivers through a human interface, optimizing visibility, dependability, and charging infrastructure control.
- **Performance Evaluation:** The system is constantly tested and optimized on the basis of major performance indicators like grid stability, energy conservation, cost saving, and user satisfaction. AI models improve their forecasts over time through reinforcement learning and adaptive optimization algorithms, promoting long-term efficiency and scalability. Feedback loops enable the system to learn and get better dynamically, opening the door to a more intelligent, more robust EV charging ecosystem.

3.2 Evaluation Metrics

- **Peak Load Reduction (L_R%)** calculates the percent decrease in peak power demand caused by load balancing. Decreasing peak loads demonstrates improved grid stability and lower strain on energy infrastructure. Where P_b and P_a are Peak power demand before and after AI-based load balancing.

$$L_R = \frac{P_b - P_a}{P_b} \times 100 \tag{1}$$

- **Load Variance (L_V)** assesses to what extent the energy demand is balanced between the charging stations. Lower variance indicates improved load balance. Where Load L_i at the charging station is considered with Average load L^- across N number of charging stations.

$$L_v = \frac{1}{N} \sum_{i=1}^{N} (L_i - \bar{L})^2 \tag{2}$$

- **Energy Utilization Efficiency (E%)** is the percentage of available energy efficiently used for EV charging to avoid wastage of energy. Where Energy E_u is drawn (used) by EVs from Total energy E_a available to the charging points.

$$E = \frac{E_u}{E_a} \times 100 \tag{3}$$

- **Cost Savings (CS%)** calculates the decrease in operational expenses once AI-based load balancing is put into practice in comparison to conventional charging. Where C_b and C_a are the cost of energy consumption before and after optimization.

$$CS = \frac{C_b - C_a}{C_b} \times 100 \tag{4}$$

- **Renewable Energy Utilization (E_U%)** calculates the percentage of renewable energy used for EV charging, which serves sustainability purposes. Where Renewable energy E_R is supplied in Total energy E_T to the charging infrastructure.

$$E_U = \frac{E_R}{E_T} \times 100 \tag{5}$$

- **Charging Time Reduction (T%)** is the percentage decrease in average EV charging time by reducing load balancing and scheduling. Where T_a and T_b are the average charging time before and after optimization.

$$T = \frac{T_b - T_a}{T_b} \times 100 \tag{6}$$

- **Grid Stability Index (G)** measures the total stability of the power grid under various loading scenarios. A higher value means good stability. Where σ_L is the Standard deviation of power load, L' is the Mean power load.

$$G = \frac{1 - \sigma_L}{\dot{L}} \times 100 \tag{7}$$

These performance measures present a quantitative assessment of how well AI-based load balancing performs in intelligent EV charging infrastructure.

RESULT AND DISCUSSION

The penetration of electric vehicles (EVs) into the power grid has posed a new challenge to charge demand management and maintaining grid stability. The conventional energy distribution system lacks scalability, real-time management of demand, and security and hence causes inefficiencies and overloading of the grid. Such limitations compromise power system stability, particularly at times of high demand when the demand on the grid is at its peak. For dealing with these concerns, this study utilizes an AI-driven architecture making use of predictive demand analysis to enable dynamic energy management. Using real-time observation and EV charging demand forecasting, the system is able to manage energy distribution and reduce congestion along with peak-hour stress. The suggested solution augments grid stability and provides for efficient, adaptive, and safe charging infrastructure with ease of integrating EVs into the power network.

4.1 Demand Prediction

The EV charging point demand forecast is examined by using actual demand alongside forecasted figures for given periods. The table outlines the precision of the AI-powered model, illustrating that forecast values are in good agreement with real demand. The results show slight discrepancies in guaranteeing safe as well as reliable energy transmission. Also, the model's best-noted error of 3% deceits in peak times of demand, which designates effectiveness in the precision of the model despite variations in charging demand.

Table 1. EV Charging Demand Prediction

Time Slot	Demand (kWh)		Error (%)
	Actual	Predicted	
00:00 - 03:00	120	118	1.67
03:00 - 06:00	95	97	2.11
06:00 - 09:00	210	205	2.38
09:00 - 12:00	330	322	2.42
12:00 - 15:00	400	390	2.50
15:00 - 18:00	350	345	1.43
18:00 - 21:00	500	485	3.00
21:00 - 00:00	250	245	2.00

From the table, peak demand is expected during peak hours between 12 PM and 9 PM. While the model forecasts a peak of 485 kWh, which is achieved at 500 kWh. This designates that the AI prediction model captures disparity in demand with barely any edge of error. The precision of the model demonstrates a small variation of 3% in forecasting energy demand, endorsing better load management and grid stability. The system can optimize energy distribution by advanced peak demand forecasting to prevent overloads and enhance overall efficiency in EV charging infrastructure.

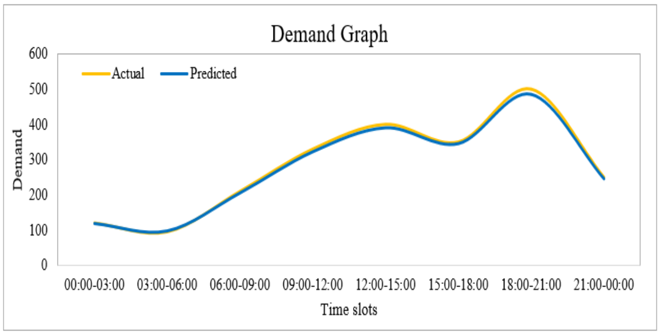

Fig. 2 Demand Prediction

The conclusions demonstrate that the demand is correctly predicted by the AI model, dropping uncertainties in energy distribution. It is a highly reliable model with an average error rate below 3%. It also reduces load distribution, averting grid overload besides saving energy wastage. The system enables the accuracy of the demand forecasting model. The figure shows energy consumed in kWh for 2000 instances.

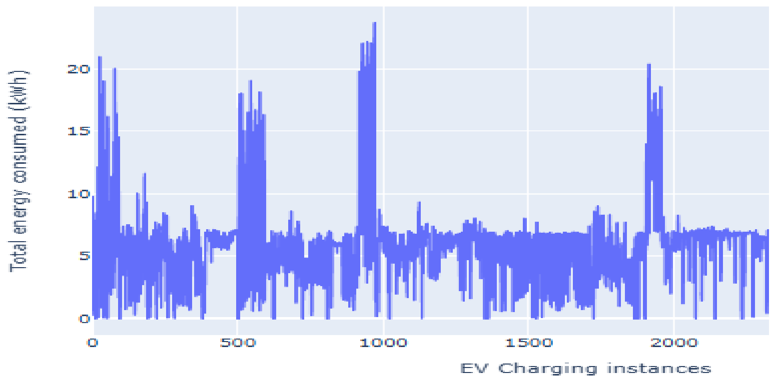

Fig. 3 Energy Consumed by EV Charging

Table 2. Prediction Accuracy of AI-Based Demand Forecasting

Metric	**Value (%)**
Mean Absolute Error	2.85
Root Mean Squared Error	4.21
R^2 Score	91.3
Accuracy	94.6

The predictive model was highly accurate, with a prediction precision of 94.6%. This means that the model accurately predicts EV charging demand with little variation from true values. The MAE of 2.85% indicates the average absolute difference between actual and predicted demand, providing dependable estimations. The RMSE of 4.21% also points to the ability of the model to reduce large errors, further enhancing demand prediction. These findings verify that the AI-driven method optimizes energy distribution efficiency and stability in the grid through less uncertainty in demand forecasting.

4.2 Load Balancing

The contrast between traditional load balancing and AI-based approaches emphasizes the broad benefits of implementing artificial intelligence within EV charging stations. In the absence of AI-based load balancing, peak load reduction is modest at 1.2%, reflecting inefficiencies in handling high-demand hours. Grid stability enhancement and energy saving are also minimal, at 0.8% and 0.4%, respectively, reflecting the weaknesses of traditional methods as shown in the table below.

Table 3. Load Balancing Efficiency Comparison

Scenario	Peak Load Reduction (%)	Grid Stability Improvement (%)	Energy Savings (%)
Without AI-based Load Balancing	1.2	0.8	0.4
With AI-based Load Balancing	27.4	19.8	15.3

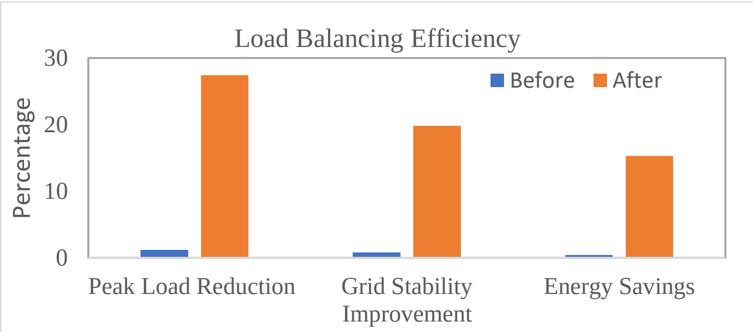

Fig. 4 Efficiency of AI-based Load Balancing Framework

This table is a comparison of the effect of AI-based load balancing with conventional methods. The AI system has a high reduction in peak load stress, improved stability, and optimized energy consumption. In contrast, using AI-based load balancing, peak load reduction is greatly improved to 27.4%, thereby effectively preventing grid overload and improving energy distribution. Grid stability improves significantly by 19.8%, providing constant power availability and lowering the likelihood of outages. In addition, energy savings increase to 15.3%, maximizing electricity use and reducing wastage. The results illustrate the effectiveness of AI-based solutions for maximizing the reliability, sustainability, and efficiency of EV charging networks.

4.3 Cost Reduction

The cost reduction as shown in the table highlights the financial advantages of using AI-based optimization on EV charging systems. Previously, traditional charging had a mean cost of $12.5 per session excluding dynamic pricing, peak loads, as well as optimal load balancing. Thus, it shows higher electricity expenses as well as inefficient use of energy.

Table 4. Charging Cost Reduction Analysis

Charging Strategy	Average Cost (USD)	Cost Reduction (%)
Previous Charging Cost	12.5	0.2
AI-Optimized Cost	9.94	20.38

However, the proposed method reduces charging costs to $9.94 per session, saving 20.38% of spending. The motivation for this saving is real-time load balancing, AI-driven predictive demand forecast, as well as scheduling optimization to evade energy wastage along with uniform distribution of charging during off-peak times. The economic viability of AI-based systems makes the adoption of EVs more cost-effective for consumers while optimizing grid usage.

4.4 Grid Stability

The grid stability results also highlight the effectiveness of AI-optimized load balancing in enhancing performance while reducing peak-period overload. As compared to traditional grid infrastructure before using AI-optimized load balancing, the AI-based model efficiently distributes energy, resulting in reduced overload during peak hours. The traditional system results in grid instability, increased risk of power outages, and inefficient use of energy while AI-optimized load balancing offers the peak-period overload reduced to 80%, with an improvement of 20%.

Table 5. Grid Stability Improvement and Overload Reduction

Metric	Before AI-Based Load Balancing	After AI-Based Load Balancing	Improvement (%)
Peak-Period Overload (%)	100	80	20.00
Grid Stability Index	72.5	91.2	25.86

The proposed system achieves dynamic energy allocation as well as predicted demand and uniformly redistributes the load across the grid capacity. Additionally, the Grid Stability Index is also boosted from 72.5 to 91.2, a rise of 25.86% in overall grid stability. These results demonstrate that AI integration enhances power distribution, as well as decreases grid pressure, allowing a better, more efficient energy system for EV charging infrastructure. The figure below illustrates the effect of the proposed system on the Grid Stability Index as well as overload during peak hours.

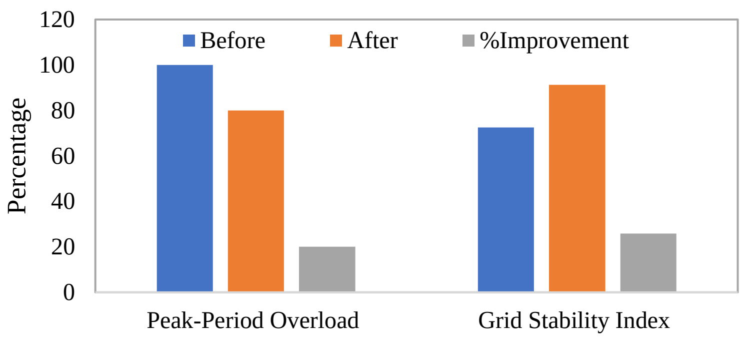

Fig. 5 Performance of Proposed Method Indicating Impact of AI-Optimized Load Balancing

4.5 Discussion

In existing studies based on a traditional tactic, electric grids are inadequate to scale the control demand in real-time or reply to safety concerns, particularly with the growing use of EV charging stations. However, the existing static or rule-based load management techniques cannot dynamically transform in response to changing demand levels. AI-based smart grid systems are a potential alternative, leveraging machine learning as well as predictive analytics to optimize energy sources. These intelligent platforms also support dynamic load balancing fulfilling the charging demand without overloading the grid. The proposed framework significantly enhances system efficacy to enable efficient EV charging. The results handle increased EV demands for energy utilization without performance degradation or congestion. In this, predictive demand analysis and adaptive load balancing, competently allocate energy resources optimally according to real-world usage patterns. The model advances energy management systems as well as ensures efficient power delivery.

Furthermore, the system put forth has a 20% decrease in peak-hour overloading, thus directly affecting the stability of the grid and optimizing overall energy efficiency. With real-time charging schedule adjustment and load spreading within off-peak hours, the system prevents power surges, reducing instances of outages and encouraging green energy usage. The conclusions present the advantages of AI load balancing in how it can effectively address significant issues such as unpredictable demand surges, wastage of energy, and ineffective utilization of the grid. Although the proposed framework has exhibited significant improvements in grid integration and load balancing, future work can further improve real-time decision-making with reinforcement learning models. Another aspect of incorporating renewable energy sources, like solar and wind energy, into the AI-based load balancing system could also enhance sustainability and minimize the reliance on traditional energy grids. Future research will also investigate multi-agent AI systems for decentralized energy management to provide more adaptive and robust smart grids that can support higher EV adoption rates.

CONCLUSION

This paper proposes an AI-powered demand response and load-balancing system for maximizing EV charging infrastructure. Through predictive demand forecasting and dynamic load balancing, the designed system greatly improves grid stability, scalability, and energy efficiency. The outcomes reflect a 20% decrease in peak-hour overload, making the smart grid more resilient and adaptive. In addition, the AI-based charging strategy lowers the cost by 20.38%, which is more economical to charge EVs. The primary contribution of this research is that it can link the dots between traditional load management techniques and AI-based smart grid optimization. Employing machine learning for demand prediction and real-time load distribution, the system addresses the most critical issues of congestion in the grid, wastage of energy, and erratic swings in demand. This study not only offers an effective and scalable solution for current EV charging networks but also paves the way for future innovation in AI-based smart energy management systems.

Though effective, the proposed AI-driven load-balancing system does have a few limitations in the form of high-quality real-time data reliance, computational intricacy, and potential integration challenges with current grid systems. Future work will look into greater real-time flexibility, integration with reinforcement learning for autonomous decision-making, and model extension to multi-energy systems for improved grid robustness and sustainability. In addition, hybrid AI-blockchain solutions will be explored further to offer security and data integrity to smart charging networks.

REFERENCES

[1] Del Pero F, Delogu M and Pierini M (2018) Life Cycle Assessment in the automotive sector: a comparative case study of Internal Combustion Engine (ICE) and electric car. Procedia Struct. Integr. 12:521–537. doi: 10.1016/j.prostr.2018.11.066.

[2] Spindlegger A, Slotyuk L, Jandric A, De Souza RG, Prenner S and Part F (2025) Environmental performance of second-life lithium-ion batteries repurposed from electric vehicles for household storage systems. Sustain. Prod. Consum. 54:227–240. doi: 10.1016/j.spc.2025.01.003.

[3] Soliman IA, Tulsky V, Abd el-Ghany HA and ElGebaly AE (2025) Efficient allocation of capacitors and vehicle-to-grid integration with electric vehicle charging stations in radial distribution networks. Appl. Energy 377:124745. doi: 10.1016/j.apenergy.2024.124745.

[4] Zhang J, Xia Y, Cheng Z and Chen X (2025) Electric Vehicles Charging Scheduling Strategy Based on Time Cost of Users and Spatial Load Balancing in Multiple Microgrids. World Electr. Veh. J. 16(1):46. doi: 10.3390/wevj16010046.

[5] Gade S, Kholpe BM, Paikrao UB and Kumbhar GJ (2025) Enriching redistribution of power in EV Charging Stations through Deep learning. Int. J. Sci. Res. Mod. Sci. Technol. 4(1):29–45. doi: 10.59828/ijsrmst.v4i1.290.

[6] Shern SJ, Sarker MT, Ramasamy G, Thiagarajah SP, Al Farid F and Suganthi ST (2024) Artificial Intelligence-Based Electric Vehicle Smart Charging System in Malaysia. World Electr. Veh. J. 15(10):440. doi: 10.3390/wevj15100440.

[7] Singh AR, Kumar RS, Madhavi KR, Alsaif F, Bajaj M and Zaitsev I (2024) Optimizing demand response and load balancing in smart EV charging networks using AI integrated blockchain framework. Sci. Rep. 14(1):31768. doi: 10.1038/s41598-024-82257-2.

[8] Ali A, Shaaban MF, Awad ASA, Azzouz MA, Lehtonen M and Mahmoud K (2023) Multi-Objective Allocation of EV Charging Stations and RESs in Distribution Systems Considering Advanced Control Schemes. IEEE Trans. Veh. Technol. 72(3):3146–3160. doi: 10.1109/TVT.2022.3218989.

[9] Naresh VS, Ratnakara Rao GVNS and Prabhakar DVN (2024) Predictive machine learning in optimizing the performance of electric vehicle batteries: Techniques, challenges, and solutions. WIREs Data Min. Knowl. Discov. 14(5). doi: 10.1002/widm.1539.

[10] Liu Z, Gao Y and Liu B (2022) An artificial intelligence-based electric multiple units using a smart power grid system. Energy Reports 8:13376–13388. doi: 10.1016/j.egyr.2022.09.138.

[11] Daneshzand F, Coker PJ, Potter B and Smith ST (2023) EV smart charging: How tariff selection influences grid stress and carbon reduction. Appl. Energy 348:121482. doi: 10.1016/j.apenergy.2023.121482.

[12] Mohseni NA, Bayati N and Ebel T (2024) Energy management strategies of hybrid electric vehicles: A comparative review. IET Smart Grid 7(3):191–220. doi: 10.1049/stg2.12133.

[13] Mohseni S, Khalid R and Brent AC (2023) Stochastic, resilience-oriented optimal sizing of off-grid microgrids considering EV-charging demand response: An efficiency comparison of state-of-the-art metaheuristics. Appl. Energy 341:121007. doi: 10.1016/j.apenergy.2023.121007.

[14] Srihari G, Krishnam Naidu RSR, Falkowski-Gilski P, Bidare Divakarachari P and Kiran Varma Penmatsa R (2024) Integration of electric vehicle into smart grid: a meta heuristic algorithm for energy management between V2G and G2V. Front. Energy Res. 12. doi: 10.3389/fenrg.2024.1357863.

[15] Memon MM, Halepoto IA, Abro MAJ and Khuhawar FY (2025) Distributed energy storage systems for distributed energy resources integration. In: Distributed Energy Storage Systems for Digital Power Systems, Elsevier, pp. 319–358. doi: 10.1016/B978-0-443-22013-5.00015-0.

[16] Bouquet P, Jackson I, Nick M and Kaboli A (2024) AI-based forecasting for optimised solar energy management and smart grid efficiency. Int. J. Prod. Res. 62(13):4623–4644. doi: 10.1080/00207543.2023.2269565.

[17] Dawn S et al. (2024) Integration of Renewable Energy in Microgrids and Smart Grids in Deregulated Power Systems: A Comparative Exploration. Adv. Energy Sustain. Res. doi: 10.1002/aesr.202400088.

[18] Shetty N et al. (2024) AI-Driven Energy Forecasting for Electric Vehicle Charging Stations Powered by Solar and Wind Energy. In: 2024 12th International Conference on Smart Grid (icSmartGrid), IEEE, pp. 336–339. doi: 10.1109/icSmartGrid61824.2024.10578078.

[19] Ahsan MS, Tanvir FA, Rahman MK, Ahmed M and Islam MS (2023) Integration of Electric Vehicles (EVs) with Electrical Grid and Impact on Smart Charging. Int. J. Multidiscip. Sci. Arts 2(2):225–234. doi: 10.47709/ijmdsa.v2i2.3322.

[20] Hossain MA et al. (2021) Multi-Objective Harris Hawks Optimization Algorithm Based 2-Hop Routing Algorithm for CR-VANET. IEEE Access 9:58230–58242. doi: 10.1109/ACCESS.2021.3072922.

[21] Rana MT, Numan M, Yousif M, Hussain T, Khan AZ and Zhao X (2024) Enhancing sustainability in electric mobility: Exploring blockchain applications for secure EV charging and energy management. Comput. Electr. Eng. 119:109503. doi: 10.1016/j.compeleceng.2024.109503.

[22] Heinekamp JF, Mendy RC, Smitmans L and Strunz K (2024) Realizing Smart Charging of Electric Vehicles at Public Charging Infrastructures Using Standards-Based Communication Architecture. In: 2024 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), IEEE, pp. 252–257. doi: 10.1109/SmartGridComm60555.2024.10738054.

[23] Manzolini G et al. (2024) Impact of PV and EV Forecasting in the Operation of a Microgrid. Forecasting 6(3):591–615. doi: 10.3390/forecast6030032.