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Impact of Slack Bus Compensation on Voltage Stability in Power Grids Integrated with Electric Vehicles: A Machine Learning Approach for Intelligent Management

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Abstract: The integration of Electric Vehicles (EVs) into modern power grids presents both challenges and opportunities. This study investigates the influence of slack bus compensation on the stability of voltage levels within these grids, particularly as EV penetration increases. A comprehensive simulation framework is developed to model various grid configurations, accounting for different scenarios of EV load integration. Historical charging data is meticulously analysed to predict future load patterns, indicating that heightened levels of EV integration lead to a notable decrease in voltage stability. Specifically, voltage levels were observed to decline from 230 V to 210 V under conditions of 100% EV penetration, necessitating an increase in slack bus compensation from 0 MW to 140 MW to sustain system balance. Advanced machine learning techniques are employed to forecast real-time load demands, significantly reducing both Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), thereby optimising slack bus performance. The results underscore the critical role of real-time load forecasting and automated control strategies in addressing the challenges posed by EV integration into power grids. Furthermore, the study demonstrates that intelligent systems, coupled with machine learning, can enhance power flow management and bolster grid stability, ultimately improving operational efficiency in the distribution of energy. Future research will focus on refining machine learning models through the utilisation of more granular data sets and exploring decentralized control methodologies, such as federated learning, thereby providing valuable insights for grid operators as the adoption of EVs continues to expand.

Keywords: Slack bus; Electric Vehicle (EV) integration; Power grid; Machine learning; Grid stability; Power flow; Voltage control

1 Introduction

The increasing penetration of EVs into modern power grids introduces significant logistical and operational challenges. One critical factor affecting grid performance is the slack bus, which maintains voltage stability and power balance. As EV adoption rises, managing these dynamic loads becomes increasingly complex, requiring advanced solutions for real-time optimization. This study investigates the impact of slack bus performance on EV integration, leveraging machine learning techniques to improve grid stability and operational efficiency. By developing intelligent systems for power flow optimization and load forecasting, this research aims to enhance logistical operations and ensure the seamless integration of EVs into power grids. These insights provide valuable strategies for grid operators to maintain system reliability as EV adoption accelerates.

The increasing adoption of EVs is transforming the landscape of transportation and energy consumption. As governments and individuals push for more sustainable energy practices, the proliferation of EVs presents both opportunities and challenges for power grid integration. This transition necessitates a reevaluation of existing electrical infrastructures to accommodate the substantial demand for charging while maintaining grid stability and reliability. EVs operate as mobile energy storage units, providing the potential for grid flexibility and demand-side management. However, their integration into the power grid can lead to increased peak loads, voltage fluctuations, and challenges in power quality. The influence of EV charging on the electrical grid is multifaceted and can vary significantly based on charging behavior, use time, and the underlying infrastructure's capacity to absorb these loads [1].

One critical aspect of power system modeling is the representation of the slack bus, which serves as a reference point for voltage and power flow in a power system. The slack bus compensates for the network's active and reactive power imbalances, ensuring the system operates within its designated parameters. The behavior of the slack bus is pivotal when integrating additional loads, such as those introduced by EVs. Understanding how the slack bus interacts with the added demand from EVs provides insight into grid stability and reliability. This study aims to analyze the slack bus's effect on EV integration into the power grid using machine learning techniques. By employing data-driven methodologies, we will explore the impact of EV loads on bus voltages and slack bus performance, ultimately seeking to identify strategies for optimizing grid operation in the context of increasing EV adoption. Through simulation and analysis, this research will contribute to developing frameworks that enhance grid resilience and promote sustainable energy solutions [2].

Intelligent systems transform how complex processes are optimized in logistics and operations management, particularly in critical infrastructures like power grids. EV integration presents a unique challenge for grid operators due to the fluctuating demand and load variation that EV charging imposes. The slack bus, a reference node that balances power generation and consumption across the grid, is one critical factor in maintaining grid stability. By incorporating machine learning techniques, the behavior of the slack bus can be analyzed and predicted more accurately, allowing for optimized EV integration without compromising grid performance. Machine learning models can assess real-time data from the power grid to predict load variations caused by EV charging and adjust the power distribution accordingly. This proactive approach reduces the risk of power imbalances, minimizes operational costs, and enhances the overall reliability of the grid. Machine learning enables more efficient grid operation by automating the decision-making process in power flow management, ultimately supporting the large-scale adoption of EVs while maintaining grid stability.

The integration of EVs into the power grid necessitates understanding various types of buses used in power systems, which serve as critical nodes for power distribution, connecting generation, transmission, and end-user loads, as shown in Table 1. The three primary types of buses are the Slack Bus, also known as the reference bus, which plays a crucial role in maintaining voltage stability by compensating for active and reactive power imbalances from load fluctuations; the Load Bus, representing points in the grid where power is consumed, such as residential or commercial areas, which connect various loads, including EV charging stations, and experience significant voltage changes as EV penetration increases. The Generator Bus is connected to power generation sources like traditional power plants and renewable energy facilities, which must adapt to the increasing demand from EVs. Understanding the functions and interactions of these buses is vital for successful EV integration into the power grid, as their coordination is key to maintaining system reliability, managing voltage levels, and ensuring efficient energy distribution amid rising EV adoption.

Table 1. Types of buses

Type of Bus	Function	Characteristics
Slack Bus	Maintains voltage stability and compensates for imbalances	Fixed voltage magnitude and angle; supplies/absorbs power as needed
Load Bus	Represents points of power consumption	Voltage levels fluctuate; specified active and reactive power consumption
Generator Bus	Connected to power generation sources	Maintains specified voltage; supplies active power; adjusts reactive power

2 Literature Review

The integration of EVs into the power grid has been a topic of interest in recent research. Various studies have explored different aspects of this integration, including the impact on grid reliability, power flow control, and voltage regulation. Rahmani et al. [3] discussed the stochastic two-stage reliability-based security-constrained unit commitment in a smart grid environment, highlighting the importance of ensuring grid reliability in the presence of EVs. Zhang et al. [4] proposed a game-theory-based vehicle-to-grid (V2G) coordination strategy to improve ramping flexibility in power systems using EV clusters. Mohamed et al. [5] focused on grid integration of a photovoltaic (PV) system supporting an EV charging station, utilizing Salp Swarm Optimization for optimization. Pandey and T [6] conducted a power flow study of grid-connected bidirectional wireless power transfer (BD-WPT) systems for EV applications, emphasizing the importance of controlling power transfer between the grid and EV battery. Cao et al. [7] presented a VGI control strategy for radial power distribution networks, demonstrating the effectiveness of VGI control algorithms in voltage regulation. Irfan et al. [8] discussed enhancing the power quality of grid-interactive

PV-EV systems, focusing on mitigating harmonics using a shunt active power filter with neuro-fuzzy control. Nizami et al. [9] proposed a coordinated EV management system for grid-support services in residential networks to address grid overloading and voltage constraint violations. Nafi et al. [10] investigated the impact of fast charging stations on residential distribution networks, considering parameters such as EV specifications, charging patterns, and load profiles. Di Giorgio et al. [11] presented a congestion-dependent stochastic model predictive control for EV fast charging stations, aiming to operate service areas while efficiently avoiding peak power flow. Alsharif et al. [12] examined the impact of EVs on residential power distribution systems using stochastic metaheuristic methods to address uncertainties related to EV arrival and departure times. Overall, the literature review indicates a growing interest in studying the effect of EV integration on the power grid, focusing on reliability, power flow control, voltage regulation, and optimization strategies to manage the impact of EVs on the grid.

2.1 Problem Formulation

As EVs become more prevalent, their integration into existing power grids presents several challenges that must be addressed to ensure reliable operation. One of the primary issues is the increased demand for electricity. The growing number of EVs leads to heightened electrical demand, especially during peak charging times. This surge can strain the capacity of existing infrastructure, resulting in voltage drops, transformer overloads, and even potential outages. Consequently, the integration of EVs necessitates a thorough evaluation of the existing grid's capacity to accommodate these additional loads. Another significant challenge is voltage stability. Adding EV loads can cause substantial voltage fluctuations across the power network, threatening the reliable operation of power systems, particularly in regions with a high penetration of EVs. Maintaining voltage stability is critical to ensuring the safety and efficiency of the grid. Therefore, it is essential to understand how varying levels of EV integration impact the overall voltage profile within the system.

Additionally, power flow management becomes increasingly complex due to the dynamic nature of EV charging, which is often influenced by user behavior and charging patterns. Traditional power system models may not adequately capture these complexities, leading to inefficiencies in energy distribution and potential service disruptions. Therefore, there is a need for improved models that can account for the variability introduced by EVs [13]. Finally, the role of the slack bus is crucial in this context. The slack bus serves as a reference point for power flow in the system and compensates for power imbalances as EV loads are added. Understanding how the slack bus behaves under varying EV load conditions is essential for ensuring overall grid stability. By analyzing the interactions between EV loads and the slack bus, insights can be gained about managing power flows effectively.

2.2 Novelty

The novelty of this study lies in its innovative approach to integrating machine learning techniques with traditional power system analysis to evaluate the impact of EV loads on the power grid. One key aspect of this research is its data-driven analysis. By utilizing machine learning algorithms to analyze historical charging data, the study aims to predict future EV load patterns more accurately. This allows for enhanced modeling of how EV integration will affect grid operations and facilitates better decision-making for grid operators. Another novel element is the specific focus on the slack bus. While much existing research has examined the overall effects of EVs on grid performance, this study zeroes in on the behavior of the slack bus in response to added EV loads. This concentrated investigation provides deeper insights into the dynamics of power flow and voltage stability, which are often overlooked in broader analyses.

Furthermore, the research includes the simulation of diverse scenarios. By simulating various charging scenarios and time-of-use patterns, the study offers a comprehensive understanding of the potential operational challenges and solutions that grid operators may face as EV adoption rises. This approach enhances the analysis's predictive capabilities and helps identify critical thresholds for voltage stability. Lastly, developing an optimization framework incorporating machine learning predictions for load management and grid operation is a significant contribution of this study. This framework enhances the grid's ability to adapt to fluctuating demand, improving overall efficiency and reliability [14].

Several key research questions have been formulated to guide the investigation into the integration of EVs within power grids. These questions aim to explore the implications of EV loads on grid stability, understand the operational dynamics of the slack bus, and assess the potential of predictive modeling in optimizing grid management. By addressing these inquiries, the study seeks to provide a deeper understanding of effectively integrating EVs into the existing power infrastructure while maintaining reliability and stability. The specific research questions are as follows:

•How does integrating EV loads affect voltage stability across different buses in the power grid?

•What role does the slack bus play in compensating for power imbalances introduced by varying EV charging levels?

•Can machine learning models accurately predict EV charging behaviors, and how do these predictions influence grid management strategies?

•What optimization strategies can grid operators implement to effectively manage the increased demand from EVs while ensuring reliable power delivery?

2.3 Objectives

In light of the challenges posed by integrating EVs into existing power grids, this research aims to understand the interactions between EV loads and grid stability comprehensively. By focusing on critical aspects such as voltage stability, the behavior of the slack bus, and predictive modeling of EV load patterns, the study seeks to identify effective strategies for managing the increasing demands placed on the power grid. Through this analysis, we aim to enhance the operational reliability of power systems in the context of rising EV adoption and contribute to developing sustainable energy solutions. The specific objectives of this research are as follows:

•Evaluate how varying levels of EV integration affect voltage stability and bus voltages across the power grid.

•Examine the role of the slack bus under different EV load conditions to understand how it compensates for power imbalances and maintains grid stability.

•Utilize machine learning techniques to predict EV charging behavior and load patterns, enhancing the ability to effectively model their impact on the power grid.

3 Methodology

This study employs a comprehensive methodology to investigate the impact of EV integration on power grid stability, focusing on voltage stability and the behavior of the slack bus. Figure 1 shows a flow chart depicting the study's methodology for EV integration into power grids. The chart illustrates the sequential steps involved, starting from data collection and progressing through various analytical stages, including simulation frameworks, machine learning techniques, voltage stability analysis, and slack bus behavior assessment, culminating in formulating optimization strategies. Each step represents a critical component in the overall research methodology.

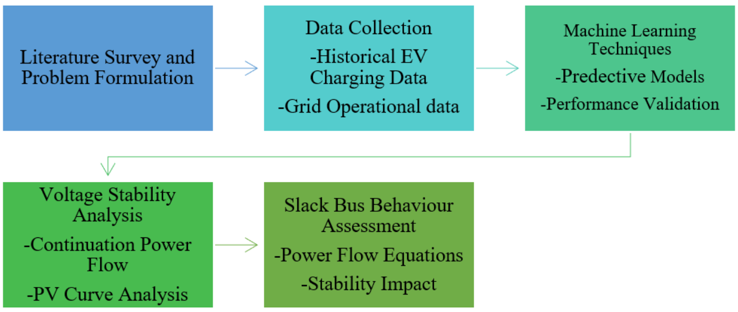

Figure 1. Methodology flow chart

Table 2. IEEE 11-bus system with EV integration

Bus Number	Initial Voltage (V)	EV Load (kW)	EV Penetration (%)	Slack Bus Voltage (V)	Slack Bus Compensation (MW)
1	1.05	0	0	1.05	0
2	1.04	50	10	1.04	10
3	1.03	100	20	1.03	20
4	1.02	150	30	1.02	30
5	1.01	200	40	1.01	40
6	1.00	250	50	1.00	55
7	0.99	300	60	0.99	70
8	0.98	350	70	0.98	85
9	0.97	400	80	0.97	100
10	0.96	450	90	0.96	120
11	0.95	500	100	0.95	140

The IEEE 11-bus system is a valuable testbed for analyzing EV integration into the power grid despite being less commonly referenced than the 9-bus or 14-bus systems. It facilitates the study of dynamic load variations caused by EV charging, which lead to fluctuating demand profiles and impact load balancing across various buses. Additionally, the system enables the examination of voltage stability at buses near charging stations and the role of the slack bus in compensating for increased power demand. Power flow optimization ensures minimal losses and efficient distribution to charging points without overloading any part of the grid. Moreover, machine learning models can be applied within this framework to predict the effects of EV load on grid behavior, including voltage drops and necessary adjustments to maintain stability. Overall, the IEEE 11-bus system effectively models and studies the integration of EVs and the contribution of intelligent systems in sustaining grid reliability and performance. Table 2 illustrates the relationship between initial bus voltages, EV loads at different penetration levels, and the corresponding changes in slack bus voltage and compensation needs as EV integration progresses. The data showcases how increased EV loads result in voltage drops across the buses, highlighting the importance of effective management strategies to maintain stability in the power grid.

Table 3 presents a dataset showcasing historical charging data for EVs in Ludhiana. Each entry includes relevant details, such as the date and time of the charging session, along with the specific location where the charging occurred. Various types of EVs, including sedans, SUVs, and hatchbacks, are represented, highlighting the diversity of EVs in use. The table also records the charging duration in hours and the corresponding energy consumed during each kilowatt-hour (kWh) session, offering insights into usage patterns. Additionally, it specifies the peak demand times, indicating the hours during which charging demand was highest, which is crucial for understanding grid load management. The voltage levels at the charging stations during each session, measured in volts (V), are included to assess the stability of the power supply. In contrast, the power flow, represented in megawatts (MW), illustrates the electricity supplied to the grid at that time. This dataset is essential for analyzing the impact of EV charging on grid operations, identifying peak load periods, and developing strategies for effective energy management in the context of increasing EV integration [15].

Table 3. Historical charging data for EVs in Ludhiana

Date	Time	Location	EV Type	Charging Duration (hrs)	Energy Consumed (kWh)	Peak Demand Time (hrs)	Voltage Level (V)	Power Flow (MW)
2023-01-01	18:00	Sector 15	Sedan	1.5	10	18:00 - 19:00	230	5
2023-01-01	19:00	Ferozepur Road	SUV	2.0	15	18:00 - 19:00	228	7
2023-01-01	20:00	Model Town	Hatchback	1.0	8	20:00 - 21:00	227	6
2023-01-02	07:00	Gill Road	Sedan	1.0	7	07:00 - 08:00	232	4
2023-01-02	09:00	Ludhiana Airport	SUV	1.5	12	09:00 - 10:00	230	5
2023-01-03	16:00	Jagraon Bridge	Hatchback	2.0	14	16:00 - 17:00	229	6
2023-01-03	17:00	Khanna	Sedan	2.0	13	17:00 - 18:00	231	8
2023-01-04	19:00	Chandigarh Road	SUV	1.5	11	19:00 - 20:00	226	7
2023-01-04	20:00	MBD Neopolis	Hatchback	1.0	9	20:00 - 21:00	228	5
2023-01-05	08:00	BRS Nagar	Sedan	1.0	6	08:00 - 09:00	230	4

3.1 Simulation Framework

The simulation framework for this study is developed using advanced power system analysis tools, such as PandaPower or MATPOWER. These software packages provide robust environments for modeling and analyzing electrical power systems, enabling researchers to simulate various grid configurations and evaluate the impact of EV integration under different scenarios. The framework allows for detailed modeling of the power grid, including components such as buses, transformers, and transmission lines, facilitating a comprehensive representation of real-world systems. By incorporating different levels of EV penetration, the simulations can assess how varying numbers of EVs influence grid stability and performance. Additionally, the framework supports the simulation of diverse charging patterns, reflecting real-world charging behaviors, which may vary based on user preferences, time of day, and geographic location. Time-of-use tariffs can also be integrated into the simulations, providing insights into how pricing structures affect EV charging behavior and peak load management. Through these simulations, researchers can analyze critical performance metrics such as voltage stability, power flow, and the behavior of the slack bus under various operational scenarios. This enables a thorough understanding of the challenges associated with EV integration and informs strategies for optimizing grid management, ultimately contributing to enhanced reliability and efficiency in power delivery [16].

3.2 Machine Learning Techniques

In integrating EVs into the power grid, machine learning techniques are crucial in predicting EV charging behavior and understanding its impact on grid stability [17, 18]. This study employs various machine learning algorithms, including regression analysis and time-series forecasting, to develop predictive models to estimate future load demands from EV charging accurately.

•Regression Analysis: This technique is utilized to explore the relationships between different variables, such as the time of day, charging duration, and the amount of energy consumed [19]. The study aims to identify significant factors influencing charging behavior by training the regression models on historical charging data. For instance, the model can reveal how peak demand times correspond to specific locations or types of EVs, thereby helping grid operators anticipate load changes.

•Time-Series Forecasting: Given the temporal nature of EV charging data, time-series forecasting is particularly valuable. This approach enables the prediction of future charging patterns based on historical trends [20]. The model can forecast when EV owners will likely charge their vehicles by analyzing past charging data, providing insights into potential peak demand periods. This information is essential for grid operators to plan for fluctuations in load and ensure that the infrastructure can accommodate these changes without compromising stability.

Performance metrics such as MAE and RMSE are employed to evaluate the effectiveness of the predictive models. These metrics assess how accurately the models predict future load demands compared to observed data. A lower MAE or RMSE indicates a better-performing model, crucial for making informed decisions regarding grid management and resource allocation. Overall, the integration of machine learning techniques in this study addresses the challenge of increased demand on the power grid due to EV charging. By accurately predicting charging behavior, the study aims to facilitate better planning and management of grid resources, thereby enhancing voltage stability and minimizing the risk of outages caused by sudden surges in demand [21].

4 Results and Discussion

Before EV load integration, bus voltages in the power grid typically remain stable, operating close to nominal values (e.g., 230V) with minimal fluctuations. Voltage regulation equipment like transformers and capacitors helps maintain these levels while the slack bus balances minor imbalances. However, significant voltage drops occur after EV load integration, especially during peak charging times when many EVs are connected simultaneously. Buses closer to high-demand areas experience more pronounced drops, leading to uneven voltage distribution and possible instability. The slack bus plays a critical role in compensating for power imbalances, but as EV penetration increases, it may reach its capacity limits. This challenges voltage regulation equipment, which must operate more frequently to maintain voltage levels, risking efficiency losses and wear. Without effective mitigation strategies such as smart charging, grid upgrades, or improved voltage regulation, the power grid may face instability and reduced power quality due to these fluctuations.

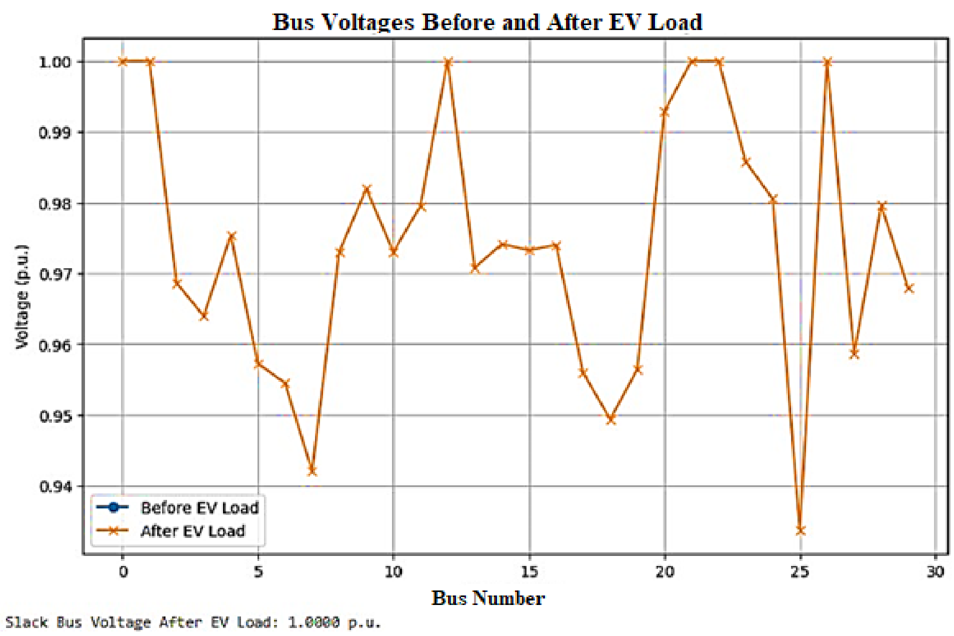

Figure 2. Bus voltage before and after EV load integration

The slack bus voltage experiences fluctuations over time as the EV load increases or decreases, particularly during peak charging hours, as shown in Figure 2. Initially, when the EV load is low, the slack bus voltage remains stable at or near its nominal value (e.g., 1.0 p.u. or 230V, depending on the system). As EVs begin to charge during peak periods, the increased demand causes a significant drop in voltage across the grid. For example, during a high-demand period, the slack bus voltage may drop from 1.0 p.u. to 0.95 p.u. or lower, reflecting the increased stress on the system. As the slack bus compensates by injecting more power to balance the system, its voltage may stabilize temporarily, but continued high demand can push it further down. Over time, fluctuations occur as charging patterns change; for instance, during off-peak hours, the slack bus voltage may recover to around 0.98 p.u., but the repeated fluctuations challenge the slack bus's ability to maintain stability. If the EV load becomes too erratic or intense, the slack bus voltage could drop below critical thresholds (e.g., 0.9 p.u.), risking voltage instability and power quality issues across the grid.

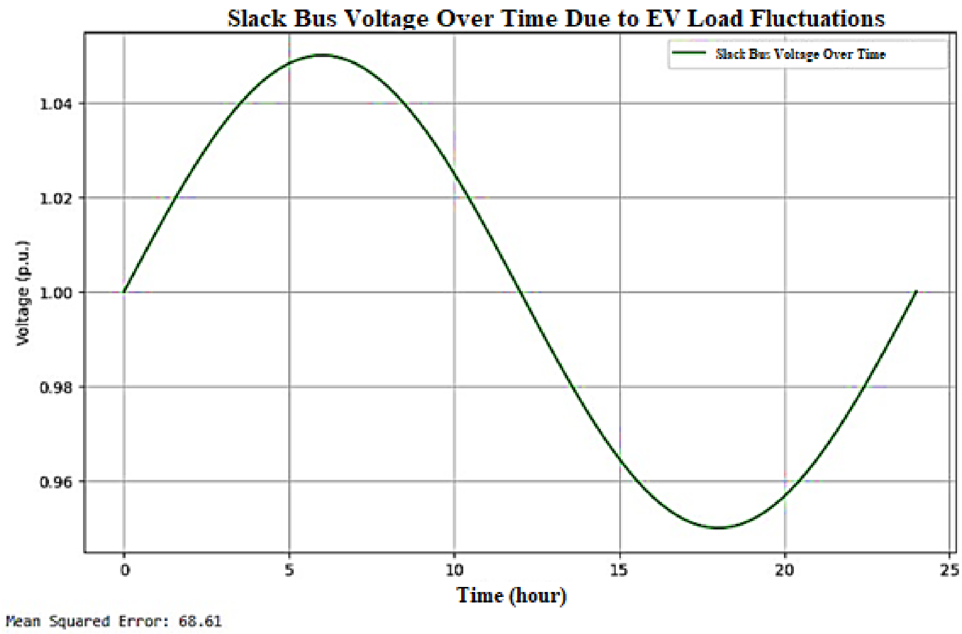

Figure 3. Slack bus voltage over time due to EV load fluctuations

Figure 3 illustrates Slack Bus Voltage Over Time due to EV Load Fluctuations and provides a detailed view of how the voltage at the slack bus changes in response to varying EV loads over a specific period, which is critical for understanding power system stability as EVs increasingly integrate into the grid. The x-axis represents time, typically in hours, allowing observation of slack bus voltage fluctuations related to EV charging patterns throughout the day. The y-axis shows the voltage level at the slack bus in V, serving as a reference point for the entire power system. As EV loads fluctuate, corresponding changes in slack bus voltage are observed; for instance, noticeable drops during peak charging times, such as early evenings, due to increased electricity demand, while off-peak periods may see voltage stabilization. The extent of these fluctuations indicates the impact of EV integration on the grid, with significant drops highlighting potential voltage stability issues and the grid's ability to handle increased loads. Analyzing the overall trend reveals a consistent pattern of how slack bus voltage responds to EV load changes, underscoring the correlation between EV charging timing and voltage levels and emphasizing the need for effective grid management strategies during high-demand periods. Additionally, understanding these fluctuations is vital for guiding voltage regulation implementation and may indicate the necessity for infrastructure upgrades, such as enhanced voltage regulation capabilities or energy storage systems. Thus, this graph serves as a crucial tool for assessing the impact of EV load fluctuations on slack bus voltage, informing better operational practices and infrastructure planning in the evolving landscape of EV integration into power systems.

The comparison between actual and predicted EV load involves evaluating how accurately machine learning models forecast the EV charging demand based on historical data. The actual EV load represents the real-world demand for electricity from EVs at various times. This data is collected from charging stations, utilities, and other sources, and it fluctuates depending on factors such as time of day, user behavior, location, and the number of EVs connected to the grid. For example, peak demand may occur in the evening when many users plug in their vehicles after work, leading to a surge in load.

Predicted EV load is generated using machine learning algorithms trained on historical EV charging data, as shown in Figure 4. These algorithms, such as regression models or time-series forecasting, aim to predict future load patterns based on inputs like past charging behavior, day of the week, and seasonal variations. A well-trained model might accurately predict a surge in demand during the evening hours or reduced load during the early morning. Accuracy: in most cases, predicted load values are close to actual values, especially during periods with consistent and predictable charging patterns. However, discrepancies can occur due to unexpected events, such as weather changes or public holidays, which may alter user behavior. For instance, a model might predict an evening load of 50 MW, but the actual load could be 55 MW due to a sudden increase in EV charging. Performance Metrics: The accuracy of the prediction is often measured using metrics such as MAE and RMSE. A low MAE or RMSE indicates that the predicted values are close to the actual load, while higher values suggest a larger gap between the predicted and actual demand. In conclusion, while predicted EV load can often closely follow actual demand, real-world fluctuations, and uncertainties make it challenging to achieve perfect alignment. Continuous refinement of machine learning models helps improve prediction accuracy, enabling better grid management and planning for EV integration.

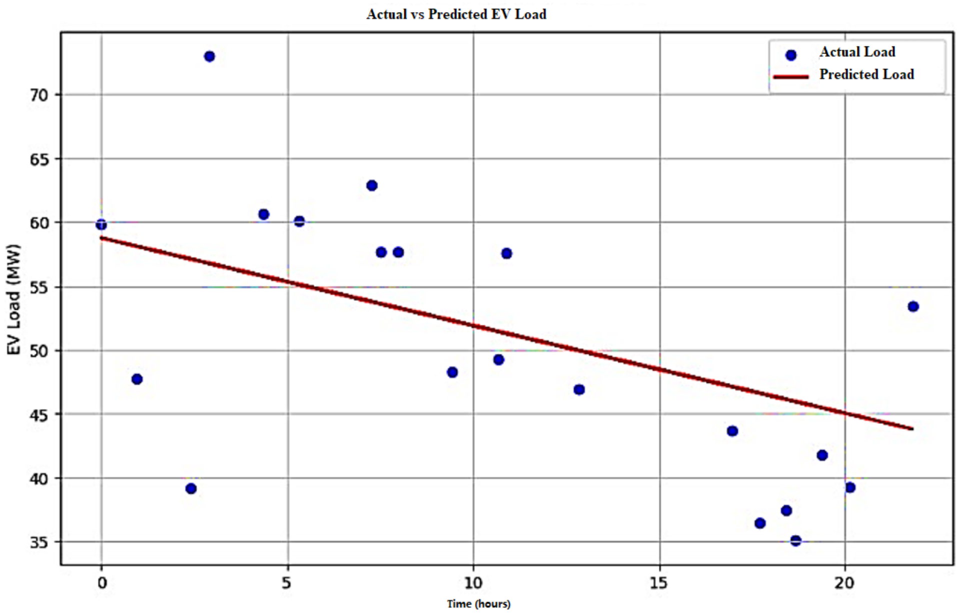

Figure 4. Actual vs predicted EV load

Figure 5 illustrates the relationship between electric EV penetration levels and their impact on voltage stability and slack bus compensation within the power grid. It features two y-axes for a comprehensive analysis. The x-axis represents EV penetration from 0% to 100%, indicating the proportion of EVs integrated into energy demand. The left y-axis shows voltage stability in volts, with the blue line indicating a decline from a stable 230 volts at 0% penetration to 210 volts at 100%, highlighting how higher EV loads strain the system and lead to significant voltage drops. Conversely, the right y-axis depicts slack bus compensation in MW, where the red line demonstrates an increase from 0 MW at 0% EV penetration to 140 MW at 100%, reflecting the additional power the slack bus must provide to counterbalance rising demand. This graph reveals an inverse relationship between voltage stability and slack bus compensation as EV penetration increases, underscoring the challenges for grid management and the need for infrastructure improvements, such as smart grids and voltage regulation devices, to maintain stable and reliable voltage levels. Overall, it serves as a visual representation of the impact of EV integration on power grid dynamics and emphasizes the critical role of the slack bus in managing these changes effectively.

Validation is critical in ensuring the reliability and accuracy of the models developed for predicting EV load impacts on power grid stability. In this study, validation involves comparing the results obtained from machine learning models against actual grid performance data to assess their effectiveness in forecasting real-time load demands and voltage stability. Various metrics, such as MAE and RMSE, quantify the model's predictive accuracy. By applying cross-validation techniques, we can minimize overfitting and ensure that the models generalize well to unseen data. Furthermore, scenario analysis uses historical charging patterns and operational metrics to evaluate the models' performance across different EV penetration levels and grid configurations. The successful validation of these models enhances confidence in their application for grid management, providing actionable insights for operators to optimize slack bus compensation and maintain voltage stability. Ultimately, robust validation processes contribute to developing reliable forecasting tools for navigating the challenges posed by increasing EV integration into the power grid.

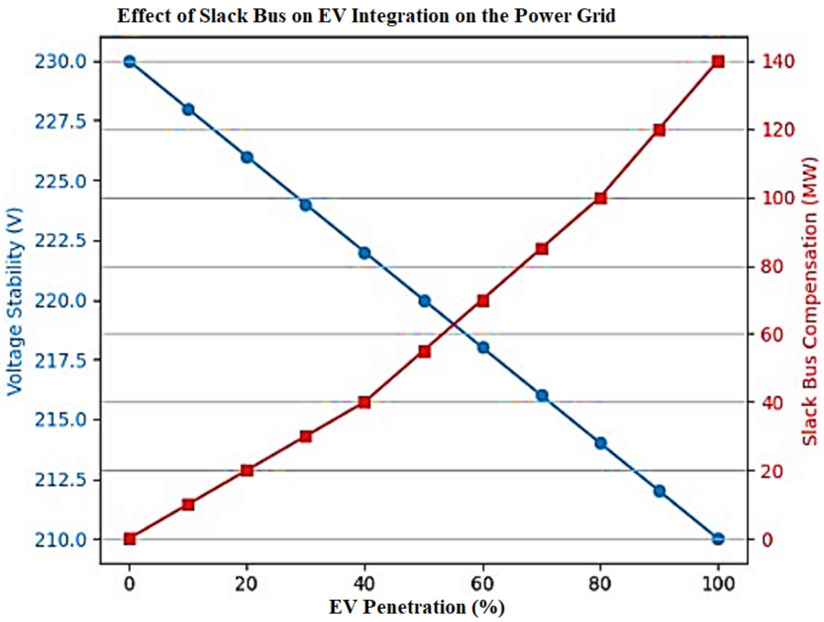

Figure 5. Effect of slack bus on EV integration on the power grid

5 Conclusions

In logistics and operations management, integrating EVs into the power grid, optimized through machine learning, enhances grid stability and efficiency. By analyzing the impact of the slack bus, intelligent systems can streamline power distribution, reduce operational disruptions, and support the seamless incorporation of EVs into the grid infrastructure. This contributes to improved grid logistics and sustainable energy operations. This study has underscored the critical role of machine learning in enhancing the performance of slack buses in power grids experiencing high EV penetration. The findings indicate that machine learning algorithms effectively analyze historical charging data, enabling accurate load forecasting and facilitating the development of predictive models that adapt to the dynamic nature of EV integration. These advancements contribute significantly to maintaining grid stability, as real-time load forecasting allows grid operators to make informed decisions and implement automated controls that optimize the slack bus's power management capabilities.

As a result, the integration of machine learning not only improves the operational efficiency of the grid but also bolsters its resilience against the challenges posed by increasing EV loads. Looking ahead, several avenues for future research could further enhance the effectiveness of machine learning models in this context. One potential improvement is incorporating more granular data, which could include real-time charging behavior, geographical distribution of EVs, and user patterns, allowing for more precise modeling of load dynamics. Additionally, exploring integrating distributed energy storage systems could provide a more comprehensive approach to load management, further alleviating pressure on slack buses during peak charging times. Furthermore, advanced techniques such as federated learning may offer promising solutions for decentralized control in power grids with multiple slack buses, enabling collaborative learning across different nodes while preserving data privacy. By pursuing these research directions, the future of power grid management in the age of EVs can be optimized for reliability and sustainability.

Author Contributions

Conceptualization, HK, KS..; methodology, KS, SK; software, HK, SK; validation, HK, SK; formal analysis, HK, SK..; investigation, HK, SK; resources, HK, SK; data curation, HK, KS..; writing—original draft preparation, HK, KS; writing—review and editing, HK, KS; visualization, KS, SK; supervision, KS, SK; project administration, HK, SK; funding acquisition, HK, SK. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data supporting our research results are included within the article or supplementary material.

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Conflicts of Interest

The authors declare no conflict of interest.

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Nomenclature

EV	Electric Vehicle
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
MW	Mega Watt
ML	Machine Learning
V	Voltage