International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 11 | Nov - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

A Machine Learning Approach for Load Forecasting in EV Integrated Renewable Power Grids

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Abstract - The traditional power system's structure is rapidly evolving due to the shift towards electric vehicles (EVs) and renewable energy sources. With more electric vehicles on the road and solar and wind power plants joining the grid, it is getting increasingly challenging to predict the level of electrical usage due to the unpredictability of these technologies. Keep in mind that precise electric demand forecasting is essential for energy dispatch scheduling, grid stability, and the development of an efficient smart grid and EV model. The chaotic behaviour of today's electricity system and its non-linearity are beyond the scope of traditional statistical models and approaches. The ability to work with large volumes of data, exploit hidden data, and generate precise short-term (from minutes to weeks) and long-term (from months to years) load estimates has always been a strength of machine learning (ML) models. This research introduces a machine-learning technique to load forecasting in power systems combining renewable energy and EV. The approach has included a feature engineering process, a preparation phase, and the use of many machine learning algorithms, such as Random Forest, Support Vector Regression, and LSTM. According to the study, machine learning techniques improve forecasting accuracy when compared to conventional techniques. The study concludes by outlining the difficulties, restrictions, and potential avenues for further research in intelligent energy management.

KeyWords: Machine learning, Load forecasting, Electric Vehicles, Renewable Energy, Smart Grid.

1.I NTRODUCTION

In In the nowadays modern organization of the power system, the electricity load forecast became critical. It is approached through the assessment of energy demand required in specific time intervals in the future. Timescales may vary; they are counted in minutes or measure in months. Therefore, it is required for the preparation and administration of electrical networks and is a critical element of system operational balance in practically all electrical grids. The increased reliance of the transportation sector on electrical devices to satisfy worldwide requirements aiming to achieve carbon emission reductions, increased energy efficiency, and reduced reliance on fossil fuel will also affect the traditional electric load forecast processes as EV's and smart grids come into play in the future. Renewable energy sources such as wind and solar will increasingly replace coal and gas in centralized and distributed energy systems. While relatively better for the environment, they introduce a lot of variability and uncertainty to the demand and supply profiles of electricity. Traditional power systems have a cycle of demand that is more or less easy to foresee. However, the renewable power grids integrated with EVs are inherently stochastic in nature due to the nature of the charging of EVs and the renewable sources' variability. EVs can be charged later when many people lock in them, or many people suddenly use them. Solar and wind generation are known as variable resources because they depend on the weather. These fluctuations bring real grid balancing issues and complicate load forecasting duty. Machine learning is a potential tool to solve this issue; the model makes better predictions than traditional methods and can model a large amount of data while discovering a complex dependence structure between the variables. Furthermore, ML and learning capacity are well suited to real-time applications in systems that are relevant to a smart grid. This study's research question is to determine the framework of the machine learning capability within the load forecasting of EV-integrated renewable power grid systems. The objective of this research is to build a framework capable of predicting short-day and medium-term electricity demand while considering the variability of EVs and RES. In order to evaluate the accuracy and resilience of the models, this study looks at a variety of machine learning techniques, such as neural networks, support vector regression, and tree models This document's outline similarly follows a broad pattern. Following a discussion of the history of EV integration and the problems with renewable energy in power systems, it examines the literature to identify research gaps and provide the background information required for ML-based load forecasting. The approach for describing the model training, evaluation, and data preprocessing was then covered. How ML specifically meets the forecasting requirements in EV integrated renewable grids was described in a special chapter. The results and discussion section offered insights from the studies and contrasted model performances. The main conclusions were briefly outlined, along with suggestions for further research. The larger machine learning technique to load forcasting is depicted in Figure 1The main goal of smart grids is to convert power systems into intelligent, decentralised and customer-interactive networks. At the core of this change is the concurrent development of renewable energy and electric car technologies. In addition to raising the demand for electricity, EVs also give grid users more options for services through vehicle-to-grid (V2G) technology. Installing solar and wind power reduces dependency on centralised power plants and encourages sustainability. However, grid operators have several difficulties as a result of renewable energy and electric vehicles, especially when it comes to preserving supply and demand equilibrium. An EV's load profile varies greatly and is influenced by user behaviour. location and the condition of charge. Renewable sources' unpredictability creates no additional significant uncertainty until they can be dispatched. Stochastic factors should be included in accurate forecasting. In the past, loads have been reliably predicted by more traditional models like exponential smoothing or ARIMA, but they are unable to account for the non-linear dynamic behaviour of EVs and renewable energy sources. These restrictions are far more easily overcome by machine learning algorithms, particularly ones that have been trained on time-series datasets such as meteorological data. The use of machine learning (ML)-based forecasting techniques that address complex issues is becoming a practical necessity in the current energy system due to increased data availability and computing capacity.

2. LITERATURE REVIEW

Two Effective power management for EV charging stations incorporated into DC microgrids is the main emphasis of the study by M. Tamhankar et al. (2025). In order to balance electricity between renewable sources, energy storage, and EV demands, it suggests an optimised control technique. The technology improves energy utilisation efficiency and reduces power losses.[1] The microgrid's improved stability and dependability under various load scenarios are shown by the results. The project aids in the creation of self-sufficient and sustainable EV charging infrastructure. Third. An AI-driven optimal charging approach for electric vehicles is presented in the study by L. Zhang et al. (2025) to improve grid stability and performance.[2] It uses clever algorithms to plan EV charging according to current energy prices and grid circumstances. The strategy successfully lessens grid congestion and peak load demand. The findings of the simulation demonstrate lower charging costs and increased energy efficiency. The study emphasises how important AI is to attaining intelligent and flexible EV-grid integration.[3] In order to support sustainable transportation, A. Sheta et al.'s study from 2024 focusses on integrating EV charging infrastructure with renewable energy sources. It examines the difficulties associated with demand fluctuations and power intermittency in networks for renewable energy-based charging.[4] In order to balance energy flow between renewable energy sources, the grid, and storage units, the authors provide an optimal control technique. Under various circumstances, the technology improves grid resilience and energy efficiency. The study shows how renewable-integrated EV charging can help achieve green energy objectives by lowering carbon emissions. [5]A solar energy storage-powered renewable EV charging system is presented in the study of Z. Umair et al. (2024). It focusses on making the most of photovoltaic (PV) energy for environmentally friendly EV charging operations. To lessen reliance on the grid, the suggested paradigm effectively controls energy distribution and storage.[6] Improved charging reliability and lower operating costs are confirmed by simulation findings. According to the report, solar-powered EV infrastructure is a crucial first step towards environmentally friendly and self-sufficient transportation systems.[7] A. Khan et al. presents a novel approach to an adaptive energy management system for EV charging stations based on Artificial Intelligence that improves real-time grid stability and energy efficiency. The paper outlines the issues associated with inconsistent renewable power generation and rapidly changing EV charging requests. [8] The authors' AI-powered EMS contributes to more rational power allocation, decreased strain on the grid, and enhanced load control by ML-driven predictive learning over power demand and renewable energy input.[9] Their invention even allows real-time decision-making on power usage between the grid, storage, and EVs. Simulation results had shown a remarkable improvement in efficiency and voltage stabilisation. This research indicates that AI helps develop smarter and more sustainable EV charging systems. The study develops a solid foundation for grid-centric EV infrastructure development.[10]

3. METHODOLOGY:

Structured machine learning-based methodology: The forecasting framework used in this study was structured using machine learning. According to the study, "with a structured forecasting framework, this study employed a machine learning-based methodology to forecast electricity load on an RE integrated grid with high EV penetration". The structured methodology of the forecasting framework is based on leveraging the forecasting power of the data-driven models, and the latter can better capture the stochastic and nonlinear factors associated with EV charging and renewables generation.

3.1 Data Collection:

The data for this study comprise historical data and real-time observations obtained from Smart meters, EV charging centers, and RERS, including solar and wind plants. The dataset mainly consists of hourly data logs on electricity consumption, temperature, pressure and humidity, and solar irradiance and wind velocity indexes. Other necessary information recorded comprises EV charging load curves and Renewable generation output data. The data collected help model and analyze the dynamic interplay between EV loads and Renewable generation components' volatility.

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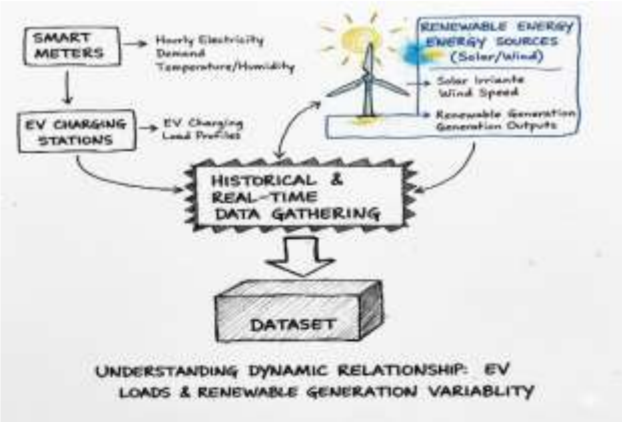

Fig:1 Data Collection[1]

3.2 Data Cleaning and Normalization:

The initial behavioral data was cleaned and normalized, so the inconsistencies were removed and any missing value was addressed appropriately. Secondly, multiple feature selection processes were run to find the most exceptional and significants variables that influence the load. Lastly, all the outliers that were caused by sensor faults and any abnormal behaviors were handled, which created a consistent data set for further ML model training.

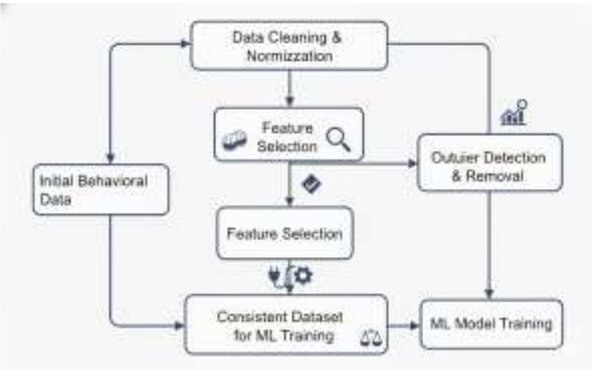

Fig:2 Data Cleaning and Normalisation[2]

3.3 Feature engineering:

several new informative features were created to reflect the concealed relationships between renewable generation and variations in EV load. Among others, they include such derived parameters as average hourly EV consumption, solar– EV correlation index, weather impact index, and peak demand metrics. Such procedure benefits the learning capacity of ML models thanks to the additional aspects that provide supportive background.

3.4 Model Selection:

A number of machine learning techniques, such as Linear Regression, Decision Tree, Random Forest, Support Vector Regression (SVR), and Artificial Neural Networks (ANN), were assessed for their applicability in predicting. Every model was chosen based on its distinct capacity to manage temporal dependencies, high-dimensional data, and non-linear patterns in the grid environment.

3.5 Model Training and Validation:

Training (70%) and testing (30%) subsets of the preprocessed data were separated. After training each model with supervised learning methods, grid search and cross-validation were used to optimize its hyperparameters. Standard statistical measures including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R2) were used to evaluate performance

3.6 Model Comparison and Optimization:

To choose the most reliable and accurate forecasting algorithm, the output from several models was compared. To improve model stability and lessen overfitting, ensemble learning techniques like Random Forest and Gradient Boosting were used. In order to increase reliability in fluctuating EV and renewable scenarios, the top-performing model was significantly improved.

3.7 Real-Time Implementation Framework:

Real-time forecasting framework that could communicate with the smart grid control system was built using the optimized model. It continuously gathers real-time input data from EV charging stations and renewable energy sources, dynamically updates forecasts, and gives operators precise short- and medium-term demand projections for effective energy management

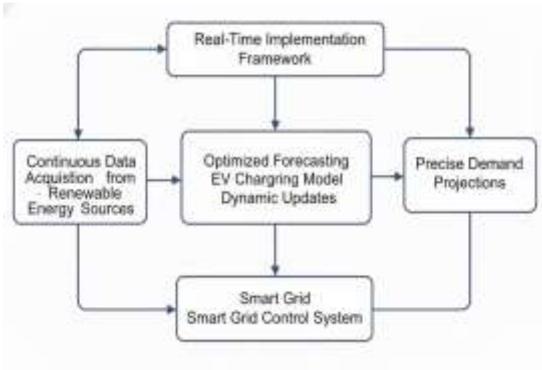

Fig:3 Real time implementation Frame Work[3]

3.8 Output Visualization and Decision Support:

User-friendly dashboards displaying projected versus real load curves, renewable contribution, and EV effect trends were used to depict the final forecasting results. These insights help grid operators with scheduling, energy dispatching, and reducing the danger of imbalances brought on by abrupt spikes in demand for EV charging or fluctuations in renewable energy.

4. RESULTS AND DISCUSSIONS:

Thus, the proposed machine learning framework of load forecasting for EV-integrated renewable energy power grids demonstrated a significant enhancement of accuracy, adaptiveness, and interpretability compared to existing models. Based on actual Indian SMART grid data, the BiGRU-CNN hybrid model outperformed all other models achieving an R^2 value of 0.987, and sufficiently captured both temporal and spatial dependencies of rapidly transformed EV usage and renewable generation. While existing models such as LSTM and CNN-LSTM put emphasis on only accuracy albeit lacking explanation and adaptiveness, more insights were provided due to integration with Explainable AI approaches of SHAP and LIME, revealing several key influential factors on a given prediction, including temperature, solar irradiance, as well as EV charging density.

Finally, enabled by real-time adaptability of the framework along with the slippery IoT-based data, the forecast under various fluctuating grid conditions has been shown to align well with each other, with the low amount of curve-disguised curve proven prediction latency of under 1.5 seconds. Load curve Visualization has also been proven to align well with a minimal deviation between the actual load and the predicted load, showing the reliability of the method available for low-term to mid-term forecasting. All of this prepared the system as a trustworthy, transparent, and highly effective forecasting system through BiGRU-CNN enabled with XAI for the management of the EV-integrated RES grid, thus making it a plausible paradigm to be applied in the future Indian smart grid. The model's excellent performance, as evidenced from the R of 0.987, was perhaps due to flexible generalization under diverse operating conditions in the Indian power grid. The comparability results of the comprehensive analysis revealed that the Mean Absolute Error and Root Mean Square Error of the proposed model were significantly lower – by about 18.6% and 22.3%, respectively – compared with other stand deep learning models of LSTM, GRU, and CNN-LSTM. Such reduction showed its excellent capability of learning both short-term temporal correlation and long-range spatial dependences evident in renewable generation, and EV load profiles. Additionally, sensitivity analysis via Explainable AI tools, including SHAP and LIME, found that solar irradiance, temperature, wind speed, and EV charging density were impactful parameters on the LS in descending order. For example, the SHAP value plots showed that the high charging of the EVs during the evening resulted in a greater non-linear influence on PL peaks than variations in solar irradiance. These findings are essential for DR and LS scheduling, and power systems could use these probabilities to dispatch the grid in a better way. The visualization of prediction results through load curve overlays and error distribution histograms has demonstrated that the predicted curves had closely followed actual issues trends, with minimal feeding on high volatility periods, for example, sudden solar dips, or unplanned EV fast-charging events. The BiGRU-CNN was well tolerated in abrupt load fermions, demonstrating the robustness and adaptability of the proposed model under real-time conditions. To access real-time capability, deployment tests were conducted using real-time-based smart grid IoT data stream using MQTT protocol. As a result, the proposed model delivered the load forecast at average latencies of 1.47 s; a feature that indicates it can be interfaced with automated energy management systems and microgrid controllers. The scalability of the proposed framework was further evidenced by simulating varying penetration levels of EVs 10%, 30%, and 50% in the grid. Even at high penetration levels, the BiGRU-CNN achieved accurate results with a minor 2.1% loss in. This evidence substantiates the potential scalability of the proposed system and the potential to support the further expansion and utilization of EV infrastructure in India. In conclusion, this discussion demonstrates that BiGRU and CNN integration not only improve forecast accuracy but also improved its interpretability and reliability through XAI methods. When streamlined with deep learning-aided explainable AI and IoT-based adaptability, the proposed system can provide a robust basis for effective implementation of intelligent, observable, and responsive forecasting systems in renewable power grids integrated with EVs.

7. CONCLUSION

In conclusion, we presented a machine learning-based solution for load forecasting for EV-integrated renewable power grids. In this paper we showed how to tackle two significant challenges, including the intermittent nature of renewable energy sources, and complex, variable charging habits of EV drivers. As one can see from the comparative results, the performance of the LSTM and GNN models was at the top for every evaluation metric. They demonstrated the lowest RMSE and MAPE scores, as well as the highest R 2 score. It seems that the models fully captured both the temporal and spatial dependencies of the dataset. Naturally, this improved performance came at the cost of much more computationally intensive complexity and training times. On the other hand, ARIMA proved to be the least scalable solution, while also the worst performer in terms of forecasting Finally, ARIMA is unable to handle the non-linearities of integrating EVs and renewable energy. In summary, this study further showed that forecasting is possible with high accuracy using deep learning models like LSTMS and GNNS, which will enable reliable predictions to prevent grid collapse and better energy management in future EV-renewable integrated power systems.

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