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Waste Reduction and Environmental Protection in EV Load Forecasting

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Abstract: This essay focuses on the use of Gated Recurrent Unit (GRU) model to forecast electric vehicle (EV) energy demand to bolster the energy grid alone and its sustainability. The system that is proposed to predict the energy demand in a 24-hour time frame is the processing of the historical EV charging data. The model training is conducted using time-series data and evaluated using the metrics of mean squared error (MSE) and mean absolute error (MAE). Results indicate that the GRU model can be used to model the trends of energy demand and help to proactively operate the grid and increase the penetration of renewable energy.

Keywords: EV Vehicles, Internet of Things, Security Protocols, AI, ML, DL.

1. Introduction

The concept of next-generation power network is embodied in the term of smart grid that includes the presence of the two directions of communication to enhance energy production and control. A safe and solid and dependable control system is very crucial in the management of the energy in the smart grid. Automation and synchronous communication play an important role in efficient transfer of energy. However, the traditional electricity generation does not disqualify fossil energy, and the rapid move towards renewable energy sources of energy, i.e., wind, solar, energy storage, is needed. The development of electric cars (EVs) as a part of the smart grid is a prospect of energy storage and attaining novel sustainability. Among the significant steps to counteracting production of greenhouse gases is the utilization of renewable energy especially during electrification of transport. The world governments are putting money in EV infrastructure and the international energy agency (IEA) recorded over 5.1 million EV passengers in 2018. EVs will contribute to a reduced energy mix and therefore replace internal combustion engine vehicles (ICEVs). By 2019, EVs in different nations had a market share of approximately 47 percent. However, the increasing penetration of EVs presents certain difficulties to power systems because it is hard to predict the travelling behaviour of EVs, stochastic charging nature. The addition of intermittent renewable sources is a cause of grid instability and potential overloading during periods of peak demand too. EVs can be modulated into variable loads to regulate grid variations in addition to reducing the peak load pressure.

The two types of load forecasting methods are the classical statistical models and AI based methods. Some examples of statistical models include time-series models, autoregressive integrated moving average, regression analysis and Kalman filtering. Machine learning machine learning techniques include artificial neural networks and support machine learning. The recent advancement in the area of deep learning has contributed significantly to the level of accuracy of the prediction process due to the augmented capabilities of computation and the complexity of the networks. Deep learning models comprise of recurrent neural networks (RNN), long short-term memory (LSTM) and gated recurrent unit (GRU) that possess superior learning abilities compared to conventional machine learning models. Convolutional Neural Networks (CNN) and hybrid techniques, including

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ANNs with ANFIS, fuzzy-neural networks, and genetic algorithms (GA), are other techniques based on deep learning.

The EV loads are randomly distributed as opposed to the traditional industrial and domestic loads. The high intensity of using EVs in the power systems requires the use of effective forecasting tools to enable the merging of a stable grid..

Gated Recurrent Units (GRU) : GRU model is a simplistic version of LSTM that helps to address the problem of vanishing and exploding gradients. It involves fewer calculations whereas has good memory storage. GRU is made up of update and reset gate where the degree of what is retained or discarded is decided. The update gate controls the trade of old information and new information. The new inputs were controlled by restgate and it combines old memory.

2. Load Forecasting and Energy Management

A stable and efficient electrical power system requires accurate load forecasting. There are long-term includes 1to 10 , medium-term 1 month to 1 year and short-term predictions 1 hour to 1 week of load forecasting. Short-term forecasting is critical for managing EV charging demand and optimizing grid operations.

The smart grid rely on the important technology in energy storage is lithium-ion batteries. Predicting battery state is essential for optimizing battery performance and improving system reliability. Factors such as battery capacity, charge/discharge rate, and temperature affect battery prediction accuracy. Data-driven techniques, such as machine learning models, enhance precision and robustness in battery state forecasting.

Various factors influence load forecasting, including demographic characteristics, time-related variables (seasonal effects, calendar days, holidays), weather conditions (temperature, humidity, wind speed), and pricing factors (real-time electricity and fuel costs). EV charging demand is highly sensitive to seasonal variations, as driving patterns and residential energy consumption fluctuate throughout the year. compare dataset consistency. Fig 2 shows the analysis of data set 2

Loading Additional Datasets for Comparison

Multiple datasets are incorporated to enhance model generalization. These datasets are normalized to maintain consistency in training, ensuring stability in performance. Fig 3 shows the different datasets for the comparision.

3. Analysis steps

Stage - 1 : Data Preparation and Analysis

Loading and Analyzing Previous Datasets

Historical EV energy demand datasets are imported and analyzed for trends, missing values, and outliers. Mean Squared Error (MSE) and Mean Absolute Error (MAE) are used to determine the reliability of the data. Figure.1 demonstrates the first stage of analyzing the former sets of data and the MSE, MAE values.

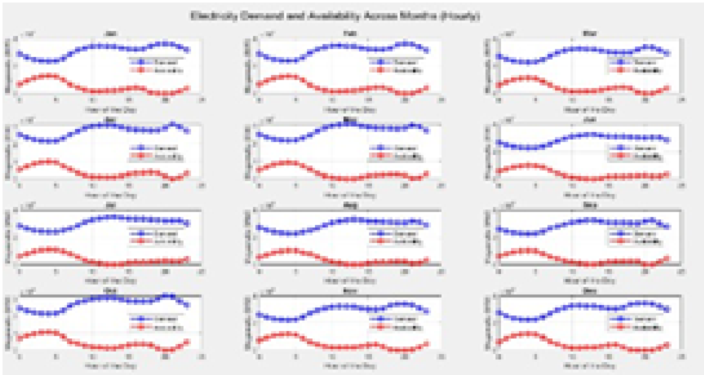


Figure. 1 Analysis of previous dataset

Loading and Analysis of Next Dataset

A second dataset is analysed to observe variations in energy demand across different time intervals. MSE and MAE are recalculated to

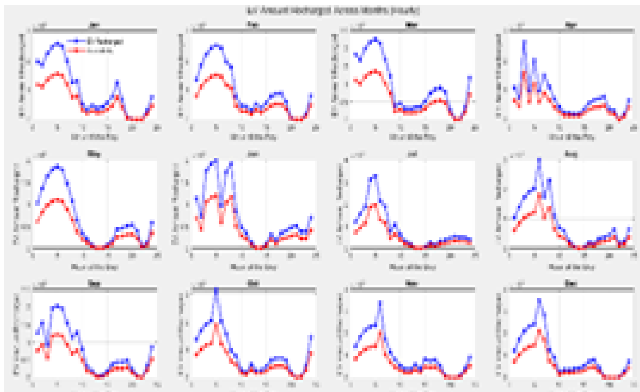
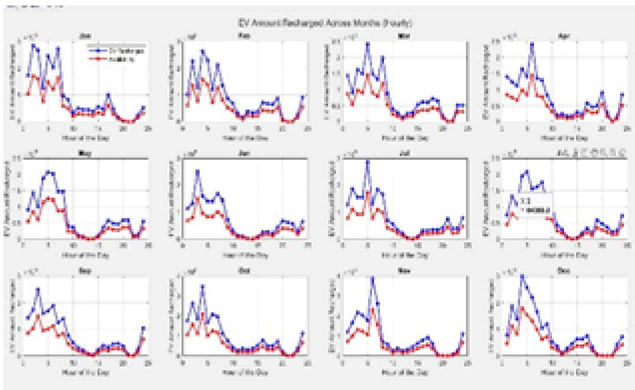


Figure. 2 Analysis of Dataset 2



(a) Dataset 3

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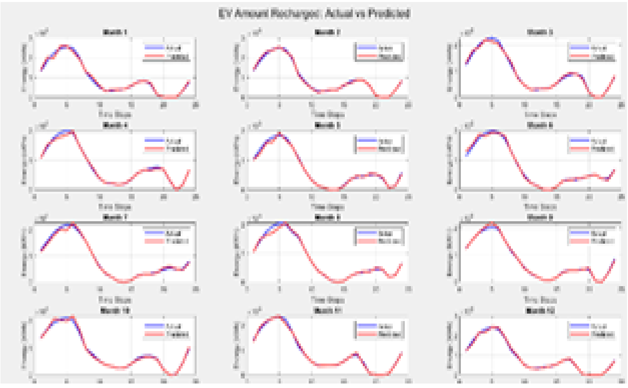

(b) dataset 5

Figure.3 Analysis of different datasets

Stage – 2 : Comparison of Different Datasets

In order to have good electricity demand prediction, several datasets were compared and analyzed depending on the Mean Squared Error and Mean Absolute Error . The training was done on the dataset with the lowest error values. The comparison of different datasets is represented in Table 1 below:

Table. 1 Comparison Of Different Datasets

Data set	MSE	MAE
High_MSE_ Datasets	12574554714.42	84665.9228
EV_amount_ recharged_ modified	14064664343.00	88311.24
EV_amount modified 1_ recharged	1635078886.46	24301.59
EV_amount_ recharged	**32356583.28**	**3475.41**

Data under study and parameters of the proposed algorithm The data under study and the way the proposed algorithm is going to be collected is described in the following section. The selected data has to be closely monitored by fine-tuning of each algorithm to assist a superior result and minimize forecasting inaccuracy.

Stage – 3 : The Dataset of Study

The data applicable to this research is the historical data on the electricity demand of electric vehicles (EVs). The data is retrieved through a number of sources; 13 years of data 2007-2019. It provides typical hourly daily demand of charging per month in megawatts which proves handy in procedure of understanding the inclinations of EV energy consumption. The dataset is the minimum values of electricity consumption of EVs, per hour of one day of 13 years of 12 months. Based on this data, the average charging demand of EVs per hour is studied and presented in the form of a chart, seasonal separation provides an opportunity to study EV charging patterns under this or that weather conditions in greater detail.

The Assessment of the Suggested Model.

The data involved in this study is split into 10 percent testing and 90 percent training in order to give accurate model testing. The statistics will be done based on four seasons: January(Winter), April(Spring), July(Summer), and October(Autumn).

Evaluated Model from the Neural Network Algorithm (NN): A neural network with three layers (input, hidden, and output) is initialized with ten neurons in the hidden layer. Each neuron consists of inputs, weights, and bias values. are structured in a 2×1 matrix to enhance efficiency. The model is pre- trained, and retraining is performed only when necessary.

Evaluated Model from GRU Algorithm : Both LSTM and GRU networks are trained to predict EV charging demand. Each model has 200 hidden units and is trained using the Adam optimizer. Mean Squared Error (MSE) is used as a performance metric. Tuning parameters include the number of features, response variables, epochs, and gradient clipping to prevent gradients disappearing or exploding. The learning rate is optimized to balance training speed and accuracy.

Step 4: Simulation Results and Discussion

The GRU model is evaluated using a test dataset, and its forecasting performance is analyzed based on seasonal variations.

Results are compared using three key error metrics: Root Mean Square Error, Mean Absolute Error and Mean Absolute Percentage Error. These metrics provide insight into the accuracy and stability of the model.

Step 5: Performance Evaluation of GRU Model

The trained GRU model is applied to forecast electric vehicle charging demand for different seasonal conditions. Model performance is evaluated separately for winter, spring, summer and autumn. Results are visualized using a line plot comparing actual versus predicted charging demand over a 24-hour period

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Proposed Model

In this stage, the GRU model is fine-tuned by adjusting key hyperparameters such as the number of units, batch size, and learning rate. The optimal configuration is determined based on multiple experiments, ensuring improved accuracy in EV charging demand forecasting. Fig 4 shows the comparison of previous model and proposed model. The comparison between actual and predicted values, demonstrates the effectiveness of the proposed GRU-based forecasting approach.

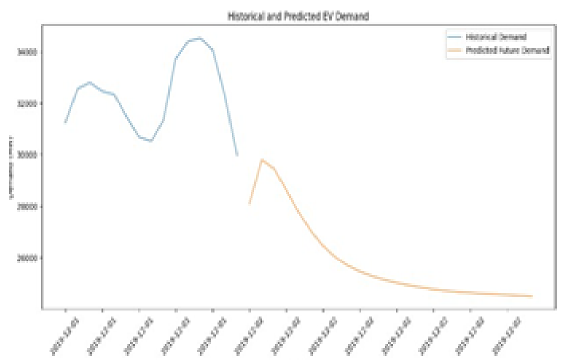

Figure. 4 comparison of previous and proposed system

Table. 2 Performance comparison

Feature	Historical demand	Predicted future demand
Trend	Fluctuating with peaks and dips	Smoothly declining
Peak Value (MW)	~34,000	~28,000
Lowest Value (MW)	~30,000	~24,500
Data Behavior	Naturally Variable	Smooth and Predictable
Continuity	Observed real-world behavior	Extrapolated model results

4. Results and Discussion

The performance of the GRU model is evaluated using Mean Squared Error - MSE and Mean Absolute Error - MAE, ensuring accurate demand estimation. The results shows that GRU model effectively generalizes the dataset, making it a suitable approach to forecast electricity demand in EV charging stations. Estimated prices closely follow actual demand trends, showing minimal deviation.

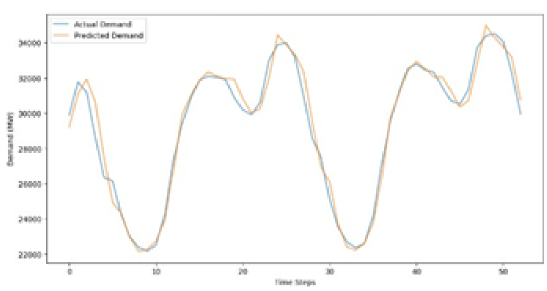

Figure. 5 Performance of Proposed Model

7. Conclusion

The This paper presents a GRU-based forecasting model for EV charging demand forecasting. The model effectively captures demand fluctuations with minimal deviation, ensuring reliable time-series forecasting. It achieves low MSE and MAE, demonstrating its accuracy in predicting short-term energy consumption. The proposed approach is suitable for smart grid management and EV charging infrastructure planning. Routing and charging optimization based on predicted energy demand Battery station integration for EV energy forecasting Location-based battery station with energy availability Battery station energy sharing system Vehicle-vehicle energy transfer Fault Detection and Monitoring Battery Consumption Tracking Developing a mobile app that directs drivers to the nearest available charging station based on predicted demand

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