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Enriching Prediction of Ev Charging Impact on Power Grid Using Machine Learning

Shubham Gade[1], Yogesh shivaji kasar[2], Vinayak Jadhav[3], Dr. Swapnil Raghunath Pokharkar[4]

[1]AI/ML Engineer, AI/ML Department, EnerSys, PA, USA
[2]Asst. Professor, Information Technology, Amrut vahini Polytechnic, Sangamner, India
[3]Head of the Department, Computer Engineering, Jaihind Polytechnic, Kuran, Maharastra, India
[4]Principal, Jaihind Polytechnic, Kuran, Maharastra, India

Abstract

Lithium mining has been extremely successful, resulting in the production of high-quality batteries across all industries. The major segment of this is electric vehicles; this is again due to fine-tuned innovations in the manufacturing of electric vehicles, which are in all senses more worthwhile than that of fossil fuel vehicles. Electric vehicles outperform fossil fuel cars in terms of mileage, resulting in lower fuel costs for the customer, reduced air and noise pollution, and numerous other advantages over traditional fossil fuel-powered vehicles. However, as we all know, every advantage also carries some disadvantages. Charging these electric vehicles often consumes too much electricity and causes severe grid failures in local and higher hierarchies. Therefore, predicting the impact on the power grid and stabilizing it through the use of smart grid technologies is crucial. This technology plays a crucial role in managing power crises worldwide. Machine learning plays a crucial role in estimating the impact on the power grid, primarily due to the significant electricity usage by EV charging stations. To deploy the model, a dataset of the charging station at the rest area in and around California is collected and weaved with the XGBoost Machine learning model and fuzzy logic concept to predict the impact on the power grid so that they can smartly manage the power crisis.

Keywords: Ev Charging impact, Power grid, Shannon Information gain, XF Boost machine learning model, Fuzzy classification.

1. Introduction

Thanks to the rapid advancements in electric vehicle manufacturing, these vehicles can achieve high mileage on a single charge. This provides customers with an exceptional driving experience, alleviating the financial burden of refueling the vehicle. This is because electric vehicles are significantly less expensive than their fossil fuel counterparts. For example, in India, Compared to fossil fuel -powered vehicles, electric vehicles (EVs) often have far lower maintenance costs.:Compared to gas and diesel vehicles, electric vehicles have fewer moving components. Less wear and tear equals lower maintenance costs and fewer visits to the mechanic. Compared to fuel cars, the annual cost of regular maintenance is usually between 1,000 and 2,000 rupees.Since electric motors do not require oil changes or air filters, we will also not have to spend money on such. In the United States, the monthly cost of gas for an SUV is around \$600, whereas the same electric vehicle costs about \$50 to \$60. This means that owning an Ev is financially friendly because it saves nearly 90% of gasoline expenditures compared to vehicles fueled by fossil fuels.

Implications include the fact that it contributes to the resolution of a long-standing issue with the electrical grid, specifically, the underutilization of power plants during the night when consumers typically use significantly less power. It is crucial that power generation and consumption be precisely matched, and battery electric vehicles (BEVs) may prove to be an extremely dispatchable electrical consumer. As additional non-dispatchable energy, such as wind and solar, is deployed, vehicle-to-grid technologies offer BEVs the opportunity to double as highly dispatchable storage. Businesses will need to install more bidirectional chargers if this is to become a reality. Since solar power is most efficient during the day, it would be beneficial to take excess power from BEVs during that time. Think of 100,000 BEVs that can be charged or discharged at 10kW using bidirectional chargers. All it takes is a few seconds for them to go from a giga watt load to a giga watt power source. The energy stored in those batteries will provide grid operators with valuable time to restore production, whether it's by waiting for the clouds to clear or by activating gas peaking plants. This is especially important in solar-heavy grids where these batteries account for half of the peak load. The majority of BEV owners won't be bothered by a charging delay of ten or fifteen minutes; however, for the small number of people who are, charge-only mode may be an option.

While current BEVs are capable of delivering or accepting far more than 10 kW, many regions simply do not have the infrastructure to support such high power demands, and rapid battery charging and discharging puts a strain on the power grid. However, it would likely be possible for an industrial site to set up stations capable of handling 350kW. Local and national power grids face opportunities and challenges brought about by the increasing deployment of electric vehicles (EVs). Although electric vehicles are better for the environment than gas-powered ones, the infrastructure may get overwhelmed during peak hours due to the high demand for charging EVs.

Power Grid Effects on a Regional and National Scale- An increase in the charging of electric vehicles might cause a surge in the demand for power, particularly during the evening and morning rush hours when many people are getting home from work. Unfortunately, this can put a burden on the electricity grid's current infrastructure. Congestion on the Local Grid - When there are a lot of electric vehicle charging stations in one place, it can put a strain on the local power grid, which can cause voltage swings and even blackouts. The reliability of the electrical grid as a whole may be affected by the widespread use of electric vehicles, especially if charging takes place all at once in big areas. As a result, the grid's overall reliability may be compromised due to frequency changes and voltage variance. Predicting the Possible Effects of Electric Vehicle Charging on Power Grids in Different Peak Demand Scenarios. The consequences of a huge number of electric vehicles charging at once during peak hours can be modeled in simulations, drawing attention to the possibility of grid overload and instability due to uncoordinated charging.

Using simulations, we can assess how well smart grid technologies like demand response programs and vehicle-to-grid (V2G) integration reduce peak demand and increase grid stability. This includes smart charging technologies as well.Optimal grid usage and reduced dependency on fossil fuels can be achieved through the integration of renewable energy sources, such as solar and wind power, with electric vehicle charging infrastructure. This integration can be evaluated through simulations.

Reducing Uncertainty in the Grid through the Use of Smart Grid Technologies - In order to reduce the grid instability that results from charging electric vehicles on a large scale, smart grid technology can be extremely helpful. Electricity providers can ease grid congestion during peak hours by offering discounts to customers who charge their EVs during off-peak hours through demand response programs.

Vehicle-to-Grid (V2G) Integration- During times of high demand, EVs can function as distributed energy storage systems and offer grid support services by feeding electricity back into the grid through V2G technology.

Intelligent Charging Network - By integrating with the power grid, smart charging stations can optimize charging times and minimize grid impact, allowing for the seamless and dependable integration of electric vehicles into the power system.

Overall, it seems that the power networks on a local and national level would be hit hard by widespread EV charging. Grid operators can efficiently handle the surge in demand, guarantee grid stability, and pave the way for a greener transportation future by optimizing charging infrastructure and deploying smart grid technologies.

[1] Zulkiflu Musa Sarkin Adar et al. showed how to predict when EVs will charge using a UK dataset and three ML models. Results for 2019 were culled from three separate public charging stations in Leeds. A description of the ML models and a breakdown of the dataset's essential components are now available. Author evaluated the models' efficacy with the help of MAE, RMSE, and R2. In order to draw conclusions on trends and patterns in EV charging behavior, this study looked at factors such as point use, usage by unique users, and usage on an hourly, weekly, monthly, and seasonal basis. Adding other features, such as weather data, is unnecessary because the features already included in the dataset are sufficient to attain high performance. Although different parameter like the beginning and ending times of charging, will be considered in subsequent works, this study only focused on charging time which may be extended to the other factors too.

[2] In the impact of electric vehicles on the transmission infrastructure of the Costa Rican power system is assessed by Gustavo Adolfo Gómez-Ramírez et al. It thinks about things like possible penetration scenarios, consumer tastes and habits, and the expected growth of car fleets. The following inferences can be made from the designed method and the assessed case study: (a) A robust methodology is necessary for the systematic and transparent analysis of the implications of EVs on a power system. The important parts and factors affecting the system's performance can then be located with this aid. b. In order to determine voltages and demand, analyses of the power system's loadability are conducted using 24-hour power flow profiles. It determines the loadability study of the transmission lines and transformer under demanding operating conditions. The discovery of problems with the electrical infrastructure begins in the year 2030.

As a result of the excessive power consumption associated with charging these EVs, local and higher-level power system outages are not uncommon. Predicting the effects on the electricity system and stabilizing it with smart grid technologies is, hence, of the utmost importance. When it comes to handling power outages, this technology is indispensable. The enormous power consumption by EV charging stations makes machine learning an essential tool for predicting the effect on the power grid. A dataset of charging stations at rest areas in and around California is used to deploy the model. This dataset is then combined with the XGBoost Machine learning model and the fuzzy logic concept. The goal is to predict the impact on the power grid and to intelligently handle power crises.

An advanced machine learning technique known as XGBoost performs exceptionally well in a wide variety of domains, including ranking, classification, and regression, among others. A great number of

applications opt for it due to the fact that it is very efficient, scalable, and produces amazing performance. XGBoost is an acronym that signifies the processing method that is commonly referred to as Extreme Gradient Boosting. This technique of ensemble learning takes the predictions of numerous weak models, which are often decision trees, and combines them to build a single model that is more accurate. In the XGBoost algorithm, the gradient boosting framework serves as the fundamental basic building element. The strategy introduces new models into the ensemble in an iterative manner, with each succeeding model concentrating on correcting the errors that were caused by the models that came before it. Hence, it is a good choice to use XG boost as the model to predict the impact on grids.
The second section of this research article, titled "Literature Survey," delves into past methodologies conducted by various researchers worldwide. Section 3 elaborates on our proposed model, which we refer to as the designed model. Section 4 of Results and Discussions elaborates on the obtained results. Section 5 concludes this research article by offering potential directions for future research.

2. Literature Survey

Using data collected from public charging stations over the course of four years, Yingqi Xiong et al. [3] offer a data-driven method for predicting the behavior of electric vehicle drivers. By combining multilayer perceptrons with K-Means clustering, a novel approach is developed and tested. Both the cross-validation and performance assessment findings show that the proposed strategy works for various charge control scheduling scenarios. After training, the proposed method may be used in conjunction with real-time control; it eliminates the need to cluster everytime a new user joins the charging network and makes tagging datasets an automatic operation.
[4] Aditya Kumar Sharma et al. highlights scheduling, prediction, and variable pricing as the three most significant components of EV management systems in their analysis. It is obvious that scheduling model performance is dependent on accurate forecasts and effective dynamic pricing schemes. The value of dynamic pricing, on the other hand, is heavily dependent on precise forecasts and effective scheduling. In the field of forecasting, the study highlights the dominance of supervised learning models, particularly LSTM and GRU. The models have received accolades for their ability to handle the nonlinear dynamics and long-term dependencies found in data from electric vehicle charging and discharging. However, the inherent uncertainty of predicting remains a concern that must be addressed by ongoing increases in model accuracy. Hybrid and ensemble methods, real-time data updates, uncertainty intervals, and other approaches have all surfaced as possible ways to enhance decision-making. In the coming time author's study will still cover a lot of ground, but it will focus more on the technical, economic, and social parts so that author can address new challenges and make the most of new opportunities. Future research should concentrate on developing better ways to forecast the power system's health, the availability of renewable energy sources, and the demand for electric vehicle charging. Machine learning has a lot of room for improvement when it comes to processing data in real-time and dealing with ambiguity; these areas might significantly improve prediction accuracy.
As per the findings of Li. Sichen et al. [5], electric vehicles are poised to be a game-changer in the automotive industry. Consumer choices can hasten the transition from gas-powered automobiles to electric vehicles. So, a strategy to decrease the charges of charging EVs needs to be developed if author want more people to purchase EVs. In order to reduce the charging expenses of electric car owners, the author proposes a DRL-based technique that combines the feature extraction capabilities of deep learning with the decision-making capabilities of RL. A decision-reduction learning (DRL) method is

employed to act upon the features extracted in the proposed approach, which uses JANET, an improved version of LSTM, as the feature extraction mechanism (FAM) to ascertain the regularity of power price volatility. After comparing the proposed solution to alternative methods, the simulation results show that it can reduce the charge cost by up to 70.2%.

[6] The work that Dan Zhou et al. are doing can have a positive impact not just on the growth of electric vehicles but also on the economic dispatch of power systems. One of their primary areas of concentration is on improving the accuracy of load estimates for electric vehicle charging stations. A Bayesian deep learning algorithm is proposed in this work as a means of estimating the unknown loads that are likely to be present at electric vehicle charging stations. Preprocessing the fundamental dataset, compiling time series data, and adding appropriate features to forecast data are the primary responsibilities of the data preprocessing unit in the method that has been proposed. In the part on forecasting, the author applies Bayesian theory to long short-term memory (LSTM) neural networks, assigns the LSTM parameters to the prior distribution, and utilizes variational inference to infer the posterior distribution. Also included in this section is the section on predicting. Based on the findings, it is clear that our Bayesian deep learning approach is capable of efficiently addressing the uncertainty problem that arises when attempting to forecast the demand for charging stations for electric vehicles.

[7] Xinhui Zhao et al. introduce the GA-GRU method to enhance energy management and electric vehicle charging scheduling. The author initially added new mutation and crossover operations to the genetic algorithm to make it better at global search and optimization. These improvements can slow down the algorithm's convergence and make it better at optimizing electric vehicle charging schedules. Secondly, the author used gated recurrent unit neural networks (GRU) as the deep learning model to predict the load on the power grid and the demand for charging electric vehicles. By analyzing historical data, the GRU model improved energy management strategies and generated more equitable charging plans by accurately predicting future charging needs. Finally, by utilizing reinforcement learning techniques, the author enhanced the timing of electric vehicle charging. Prospective future research directions include studying how different charging infrastructures and policies impact the method's performance, testing the method's ability to manage bigger datasets and more complex scenarios, and integrating other new technologies such as blockchain and edge computing. Since the authors think our proposed GA-GRU method has a lot of room to grow in smart grid EV charging scheduling and energy management, they hope our study will spur more investigation into these topics.

Arif Nur Afandi et al. [8] brought forward the idea of electric vehicle (EV) integration into the power infrastructure. Working together, the producing units adhere to a committed power production plan that allocates power output based on load demand at a given instant; thus, operating constraints must be maintained to accommodate varying loads throughout the day. With the addition of EVs as a variable load, trip patterns for mobility impact power system operation.

Research and evaluation have been conducted on the potential effects of electric vehicles on the low voltage grid. [9] Noradin Ghadimi et al. provided a complete account of the current status of electric car technology. Author have also used DIgSILENT PowerFactory's stochastic models of a low-voltage grid to look at the effects. Overall, the results are comparable; yet, this study distinguishes out from the others because of the extra contributions it offers—its stochastic approach and the broader network it analyzes.

[10] As Muddsair Sharif et al. show, the concern raised in the research about the increasing number of electric vehicles can adversely affect various other sectors. The primary factor influencing the owner-

ship of an electric vehicle is the increased use of natural resources in the production of electricity. This article's study optimizes the smart charging system for electric vehicles, which makes real-time charging decisions using DRL while also taking into account other factors. Authors successfully demonstrate in the simulated environment that the presented system outperforms other existing systems based on numerous parameters. The system includes parameters such as the cost of charging, grid load reduction, customer type preferences, and the energy efficiency of the charging stations. Author successfully demonstrates in the simulated environment that the DRL technique reduces the cost of charging electric vehicles by fifteen percent by easing the grid's load. In the future, the proposed model needs to be tested in the real-time scenario by considering other factors too.

[11] Sakib Shahriar et al. provided a technique to estimate the time duration of electric vehicle charging time and power consumption, which are linked with the scheduling of the charging of electric vehicles. The author considers past charging data, along with various parameters such as weather, traffic, and other factors. Four well-known machine learning models and two ensemble learning models were trained by the author to predict the charging pattern on the ACN dataset. [12] Mostafa M. Shibl et al. worked on an adaptive RL plan for Electric vehicle charging management and strategy. This includes both normal and fast charging stations along with vehicle to grid technique. After the thorough testing in the real world scenario and uncertainty analysis it is confirmed that the RL model is good in measurement of the magnitude as well as temporal power prices in EV charging environments. The effect of other load-specific characteristics, like rating, inductance, resistance, and quality factor, can also be studied. Finally, the RL model can be adjusted to meet all of the utility's requirements for a practical evaluation of this type of model.

[13] In the article by Tehseen Mazhar et al., they highlight how technological progress in the field of information and communication is crucial to the global spread of smart cities. Every city that is experiencing rapid growth must have a smart grid. Numerous organizations, both governmental and private, are pushing for electric vehicles (EVs) to combat climate change and reduce greenhouse gas emissions. Modern, complex power networks have encountered a number of unanticipated challenges due to the proliferation of electric vehicles. Two important issues are the search for more efficient ways to charge consumers and the introduction of technologies that can reduce costs while controlling energy supply and demand. According to Mouaad Boulakhbar et al. [14], in regulated energy markets, electric vehicle charging stations significantly impact the market due to their frequent use of high power during peaThe experiment considers two charging stations in Morocco, with the aim of collecting 2000 observations. observation data. Deep learning models such as ANN, RNN, LSTM, and GRUs then utilize the collected data. Author evaluates the performance of these models based on specified criteria after the training process.

[15] Yanning Li et al. utilized grid and EV-side geographical and temporal data in order to determine the potential impact that the increased demand for electric vehicle charging could have on the electric distribution infrastructure in the state of California.

After conducting research on the impact that electric vehicle charging stations have on the power grid, Kadir Olcay et al. [16] came up with three of the most important points. Because electric vehicle charging stations have non-linear demands, it is believed that the transformer will be damaged as a result of their presence. [17] Paul Eitel and others, among others It is not possible to use the trial region, which is more rural than the rest of Germany, as a standard for the entire country. This can occur during the charging process of the electric vehicle. However, the study's findings do not apply universally to metropolitan settings. There is a possibility that additional research into this subject could shed insight on the ways in which electric vehicle charging habits in highly populated urban areas disrupt the power system.

3. Designed Model

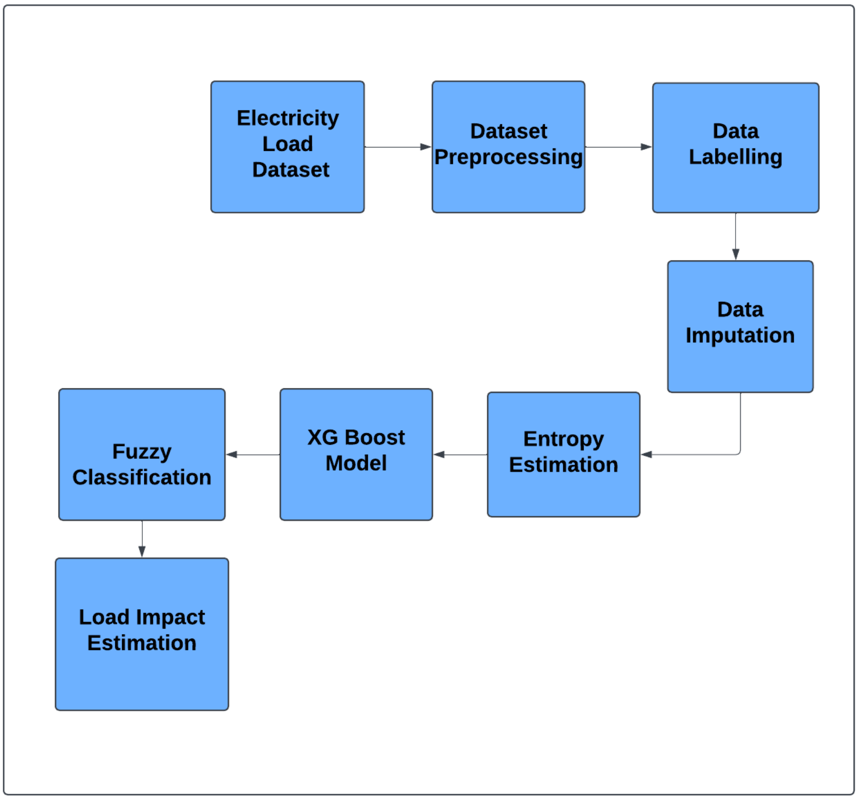

Figure 1: Proposed model for Load impact estimation on grids

Figure 1 below illustrates the proposed methodology for measuring the impact of widespread electric vehicle charging on power grids. We narrate the steps in detail below to achieve the prediction.

Step 1: Dataset Processing - For the prediction of the impact of EV charging on power grids, the proposed methodology utilizes the dataset from the following URL: https://www.kaggle.com/datasets/pythonafroz/electric-vehicle-charging-impacts-of-r-energy. This dataset contains the some attributes which are elaborated as follows - ‘Rest Area Name’ – which indicates highway rest stop names in and around California. The next attribute is ‘Region’ which contains the abbreviations of the regions in and around California. ‘Utility provider’ attribute indicates the electric power company that is providing service in the mentioned region. The 'Route type' attribute specifies the route that the 'utility provider' uses to install the electric cables that connect to the 'Rest Area name', which is having three values like US route, Interstate, CA state route, The next attribute indicates ‘latitude’ and ‘longitude’ of the ‘rest area name’. This is followed by the other attributes like ‘AADT’ (Annual Average Daily Traffic), ‘AADT Year,’ and ‘Caltrans No.’ provided to the ‘rest area name.’ Attribute ‘Total L2 Chargers’ indicates the number of level 2 charging options, followed by ‘Total L2 Capacity (KW),’ ‘Total DCFC’ (direct current fast chargers), ‘Total DCFC Capacity (KW),’ and finally ‘Total Installed Capacity (KW).’

Step 2: Dataset Preprocessing - In this step, we download the dataset and use its root path to read in a double-dimension object from the Python pandas library. We use the obtained dataset object to eliminate unwanted columns such as ‘region’, then reframe the dataset object using the same reference. To ensure the dataset object formed properly, its head and tail rows with the size of 5 are printed and rechecked. This process entails describing each attribute of the dataset, including parameters such as mean, standard deviation, 25%, 50%, 75%, 100%, minimum, and maximum values, using the describe method in Python. And also a histogram of each attribute is obtained to view the distribution factors of the same to ensure the quality factor of the data.

Step 3: Dataset labelling and imputation - The preprocessed dataset object is analyzed for the data type of each of the attributes and the object type, which is actually the string type, that are used for labeling by using the label encoder of the scikit-learn library of Python. After labeling, we convert all data into numerical form and impute the missing values to strengthen and stabilize the dataset. An oversample object for the dataset is created to estimate the total missing data in each attribute along with the percentage. Then oversample each attribute filled with mode 0 with fillna() to use by the iterator called IterativeImputer() to get the mice imputer object. After fitting the transformation for the oversampled object, the mice imputer object measures the interquartile range (IQR), a statistical tool that identifies outliers in the data by considering the context of mutation. After all this process the following equations 1, 2,3 and 4 are used by the IQR to impute the missing values in the dataset.

$Q1 = fxm(0.25)$ ____(1)

$Q2 = fxm(0.75)$ ____(2)

$IQR = Q2 - Q1$ _____(3)

$fxm = (fxm < (Q1 - 1.5 * IQR) \mid fxm > (Q1 - 1.5 * IQR))$ ____(4)

Where

fxm - Mice imputation function

IQR - interquartile range

Next, we measure the correlation between each attribute in the imputed dataset to create a correlation matrix by using the Pearson correlation model. Based on this, the highest correlated attributes are selected for the further process of the boost model.

Step 4: Entropy Estimation – Shannon information gain (IG) is a metric that is used to measure the degree of uncertainty that is reduced regarding a target variable as a result of the utilization of a feature. This technique is widely used in the field of information theory for the purpose of feature selection, particularly for the purpose of removing noisy features.

The list containing the imputed data is utilized as an input in this step of this procedure. This procedure allows the evaluation of the information gain values of the attribute for the evaluation of the entropy. These values facilitate the distribution factor of the attribute like ‘total L2 capacity’ and ‘Total DCFC Capacity (KW)’ which is a useful metric for the further determination of the load on the power grid.

Each of the attribute value is utilized for the calculation of the scalar weight. This is done by utilizing the attribute count and the frequency to determine the information gain through the Shannon Information Gain equation given below in equation 5.

$$IG = -\frac{P}{T}\log\frac{P}{T} - \frac{N}{T}\log\frac{N}{T} \quad \_\_\_\_\_ (5)$$

Where
P= Matched number of the attribute L2 capacity and Total DCFC Capacity
T= Total capacity
N= T-P
IG = Information Gain for Comment
The evaluation of the Shannon Information gain through the equation above yields values between 1 and 0. Any value closer to 1 indicates a higher distribution factor and values closer to 0 depict smaller distribution factor. The gain list is created by storing these values along with the service provider and then sort the list to drop 25% of the data, the further obtained data is used to implement the XG boost model.
Step 5: XG Boost model: The obtained data from the past steps are used here to train using extreme gradient boosting model. In this case, in order to select the features, we apply the minMaxscaler function on the data that has been preprocessed and imputated. How much the minmaxscaler is worth It is necessary to change the characteristics by scaling them to a range that we specify. It is the responsibility of this estimator to do its own scaling and translation for each feature on the training set in order to get it inside the specified range, which might be anywhere from 0 to 1. MinMaxScaler does not lessen the influence of outliers, despite the fact that it linearly scales the outliers into a predetermined range, where the data point with the greatest value represents the greatest value and the data point with the smallest value represents the minimum value. This process results in the production of two lists: one list has the labels (Y), while the second list contains all of the additional features (X). The minmaxscaler transformation is represented by equations 6 and 7, which may be found after this paragraph.

$$x_{std} = \frac{(x - x.min(axis=0))}{(x.max(axis=0) - x.min(axis=0))} \_\_\_\_\_\_\_\_ (6)$$

$$x_{scaled} = x_{std} * (max - min) + min \quad \_\_\_\_\_\_ (7)$$

where min, max = feature_range.
Within the Sklearn package, the train_test_split() method generates four lists: y_train, y_test, X_train, and X_test. These lists are derived from the parameters, as well as the data from the X and Y feature lists. For the goal of training the model, the Y_train and X-train datasets are utilized, whilst the Y_test and x_test datasets are utilized for the purpose of autocorrection continuously during the training process. As a means of constructing an accurate model, we train the neural network on eighty percent of the data and then test it on twenty percent of the data. After that, we implement the minmaxscaler() function from the Sklearn package in order to scale the data points such that they remain within the range of 0 to 1. An efficient training of the lists X_train and Y_train is accomplished by the utilization of a bi-directional XG Boost model.
In XG Boost Adjusting the learning rate in order to acquire the step size shrinkage is necessary in order to prevent overfitting from occurring during the process of training the XG boost model using the data that has been provided. It begins at zero and ends at one. First, we will need to set max_depth to determine the greatest depth that each tree is capable of developing during any given boosting round. After that, we will need to set subsample to determine the sample proportion for each tree. In situations when the subsample value is low, underfitting may take place. Through the subsequent XG boost step, which

is called colsample by tree, it is possible to determine the percentage of features that are utilized for each tree. In the following step, we will set the n estimators parameter, which will determine the number of trees that we will be constructing. An excessively high value for this parameter may result in overfitting. The objective is to acquire a measurement of the additional loss function of the XG boost model. In order to determine whether or not a particular node will split, the gamma property takes into account the anticipated decrease in loss that will occur following the split. If the value is higher, there will be less splitting. Support for it will only be provided to learners who are based on trees. L1 regularization for plant weights is what we get when we utilize alpha as a regularization method. A greater degree of regularization takes place when its value is high. In comparison to L1, which is known as L2, Lambda offers a regularization procedure that is more smooth. This is the case for leaf weights. After adjusting all these parameters, the fit function trains XGBoost to predict the parameters of the electricity load on service providers. These load parameters are further analyzed fuzzy logic to estimate the impact in the next step. The general architecture of XG boost is represented in the below figure 2 as mentioned in [18].

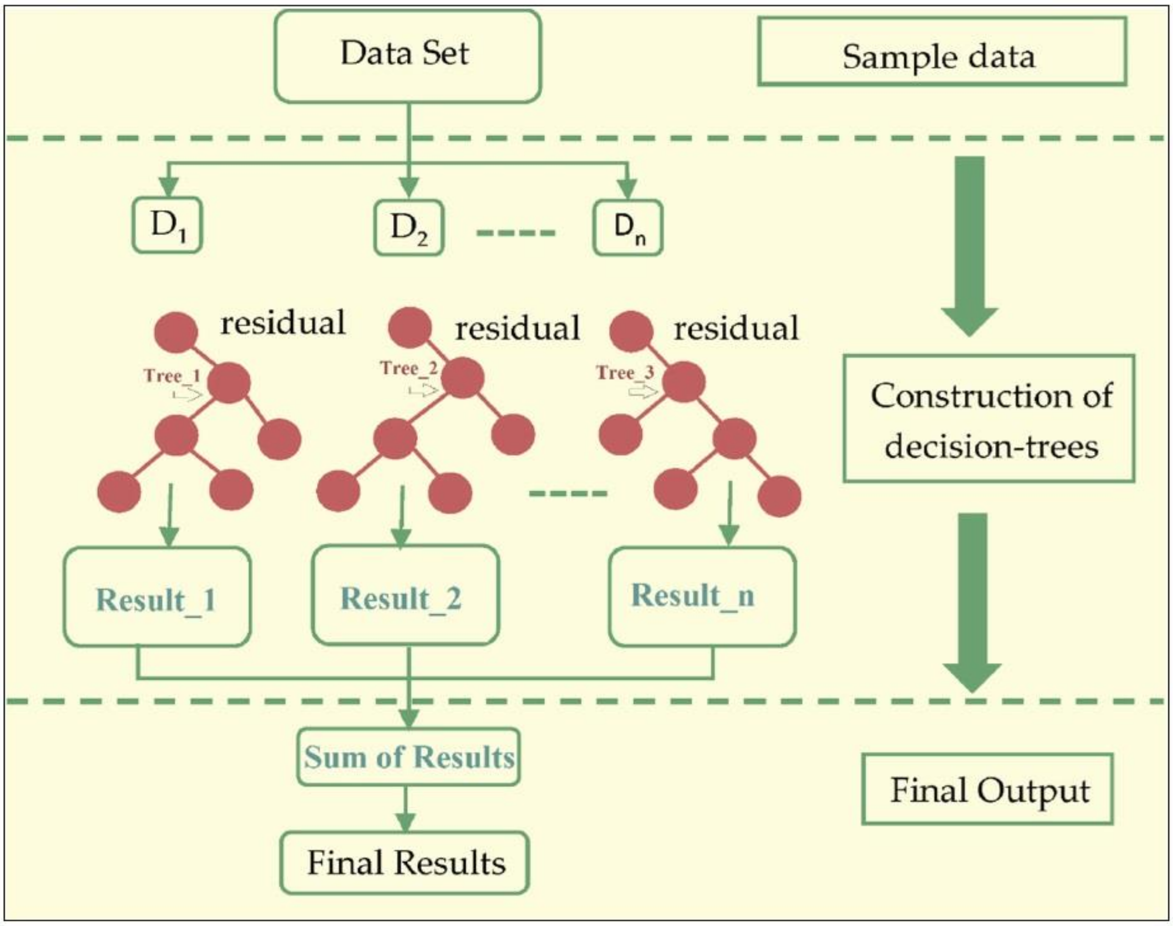

Figure 2: XG Boost model general architecture

Step 6: Fuzzy Classification - To aid effective classification of the predictions score values achieved in the previous stage as an input to quantify the influence on power grids, the fuzzy classification approach is applied. This approach is used to facilitate accurate classification. The objective of the fuzzy classification strategy is to achieve an effective improvement in the classification impact procedure by utilizing fuzzy crisp values. This is accomplished through the utilization of fuzzy crisp values using the

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fuzzy classification approach. By utilizing the likelihood scores, these values are able to achieve five different segregations, which are as follows: VERY HIGH, HIGH, MEDIUM, LOW, and VERY LOW. After that, these variables are utilized to categorize the prediction scores into five unique segregations, which are then shown to the user in a graphical user interface (GUI).

4. Results and Discussions

A Windows-based GPU machine with an Intel Core i7 processor deploys the developed architecture to measure the impact of EV charging on the power grid. The machine boasts 32 GB of primary memory and 1 TB of secondary memory. We host IDEs like Jupyter Notebook and Spyder IDE in the Anaconda repository. As we mentioned in the previous section, the machine learning model XGBoost is used to estimate the prediction scores; the training and testing accuracy obtained from the XGBoost model are depicted in figures 3 and 4, respectively.

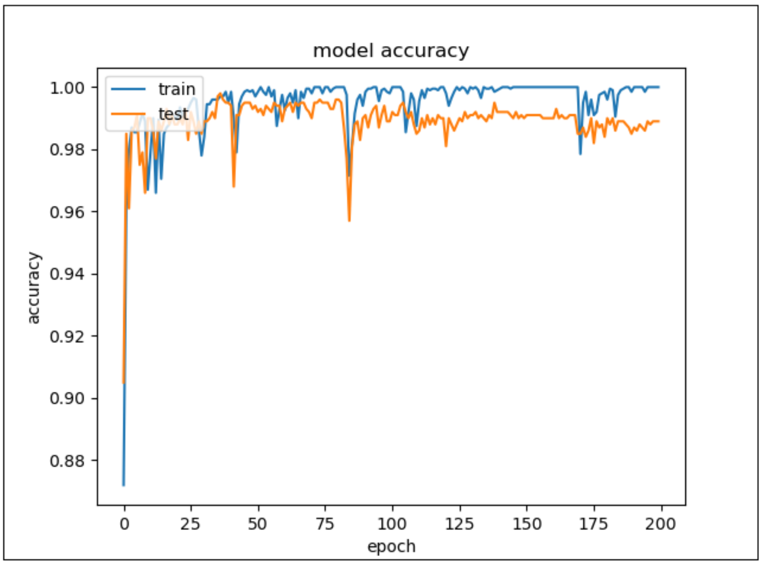

Figure 3: XGBoost model accuracy graph

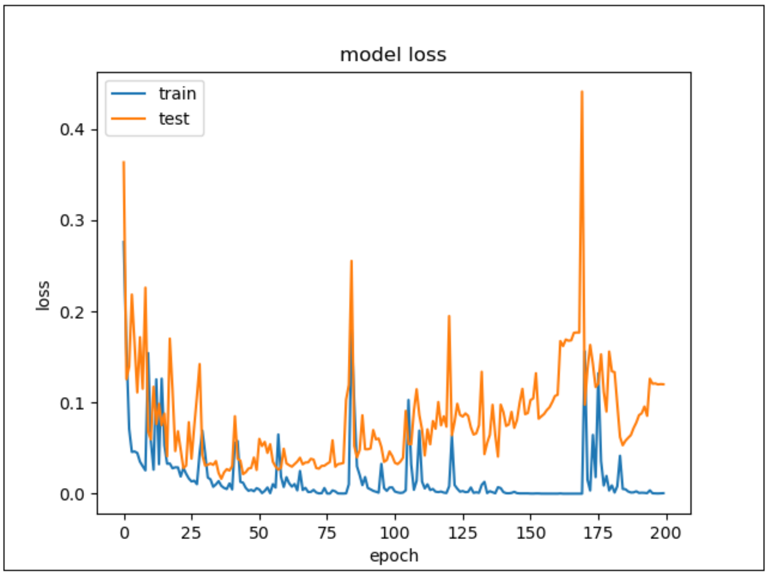

Figure 4: XGBoost model Loss graph

On observing the above graph, it is evident that the XGBoost accuracy is almost touching 100% and with loss inversely related to the accuracy. This indicates that XGBoost works well in the prediction of the EV charging impact on the power grids for the given dataset.
We tested the carried experiments to obtain precision and recall based on the provided equations.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad -(8) \qquad \text{Precision(P)} = \frac{TP}{TP+FN} \quad -(9)$$

$$\text{Recall(R)} = \frac{TP}{TP+FP} \quad -(10) \qquad \text{Macro} - \text{F1} = \frac{2*P*R}{P+R} \quad -(11)$$

Where , TP stands for true positive values of the prediction, TN for true negative values, FP for false positive values, and FN for false negative values. The obtained precision, recall and F measure graphs are depicted below in figure 5,6,7,8 and 9.

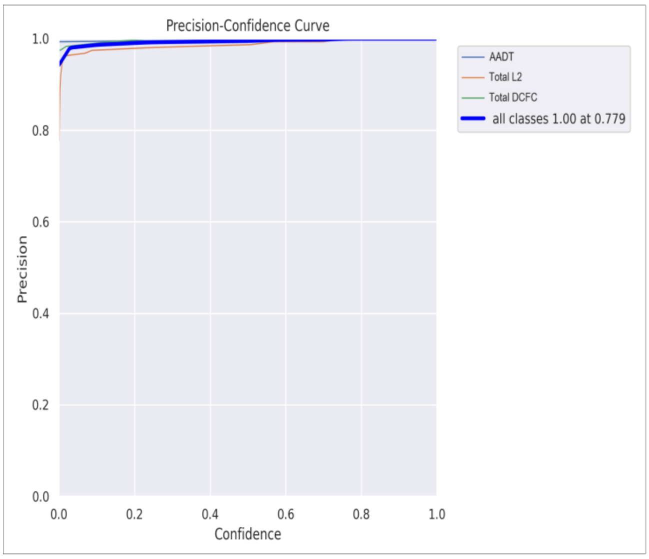

Figure 5: Precision Confidence Curve

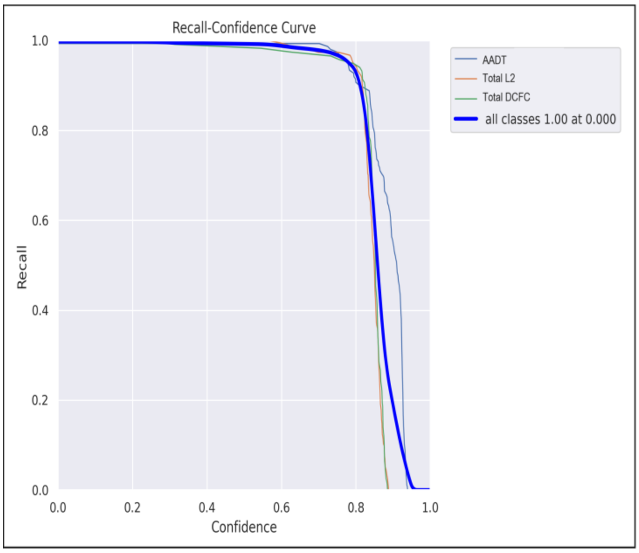

Figure 6: Recall Confidence Curve

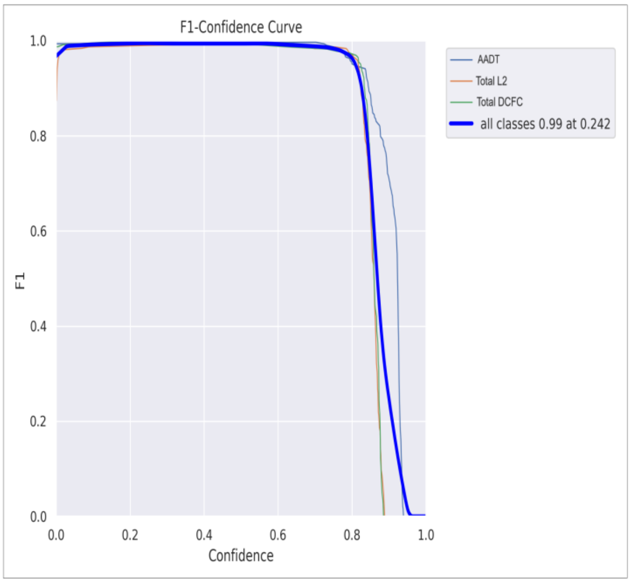

Figure 7: Precision-Recall Curve

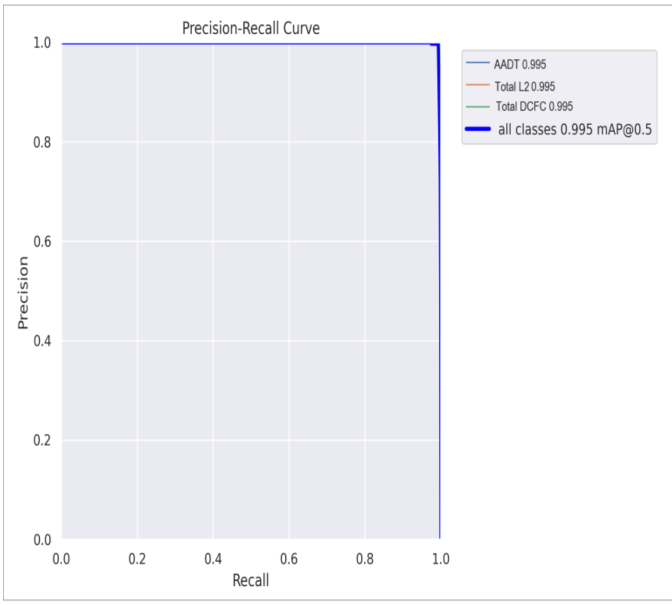

Figure 8 : F1- Confidence Curve

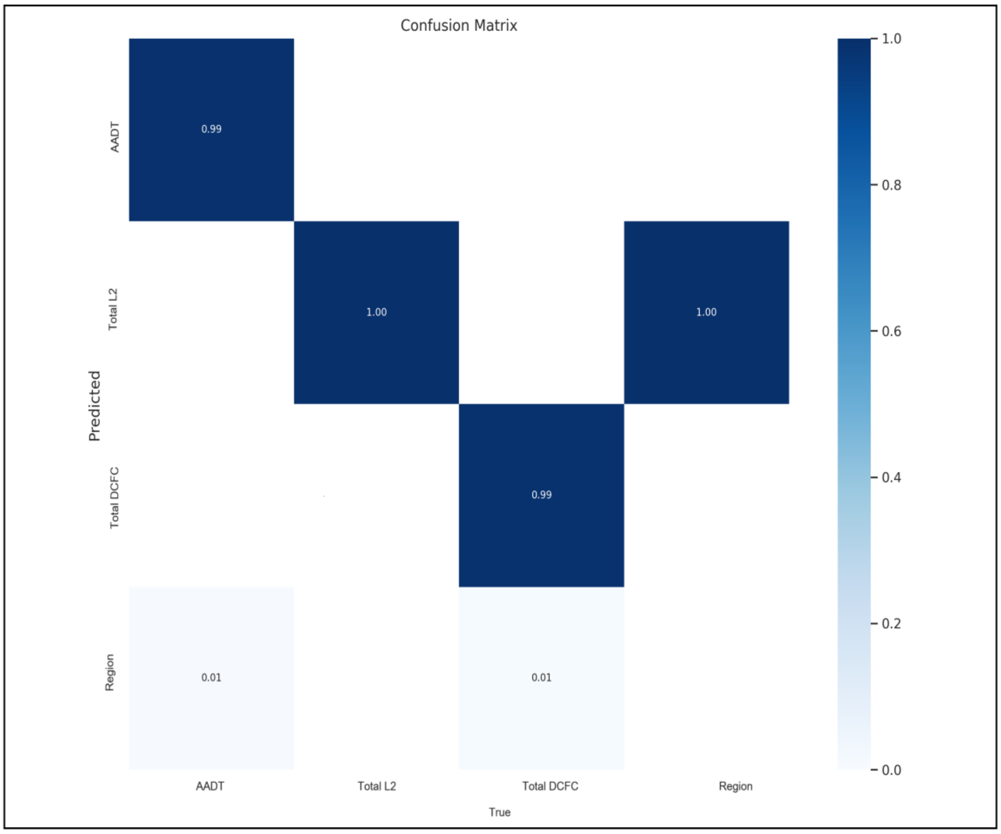

Figure 9: Confusion matrix obtained for the prediction

On observing all the plots in the above figure 5 to 9, its summary is captured in the below table 1, and a subsequent graph is plotted in figure 10.

Parameters	AADT	Total L2 (In KW)	Total DCFC (in KW)
Precision (%)	99.5	99.5	99.5
Recall (%)	99.5	99.5	99.5
F-measure (%)	99	99	99
Precision Confidence (%)	100	100	100
Recall Confidence (%)	100	100	100

Table 1: Summarized Result parameters of the experiment results

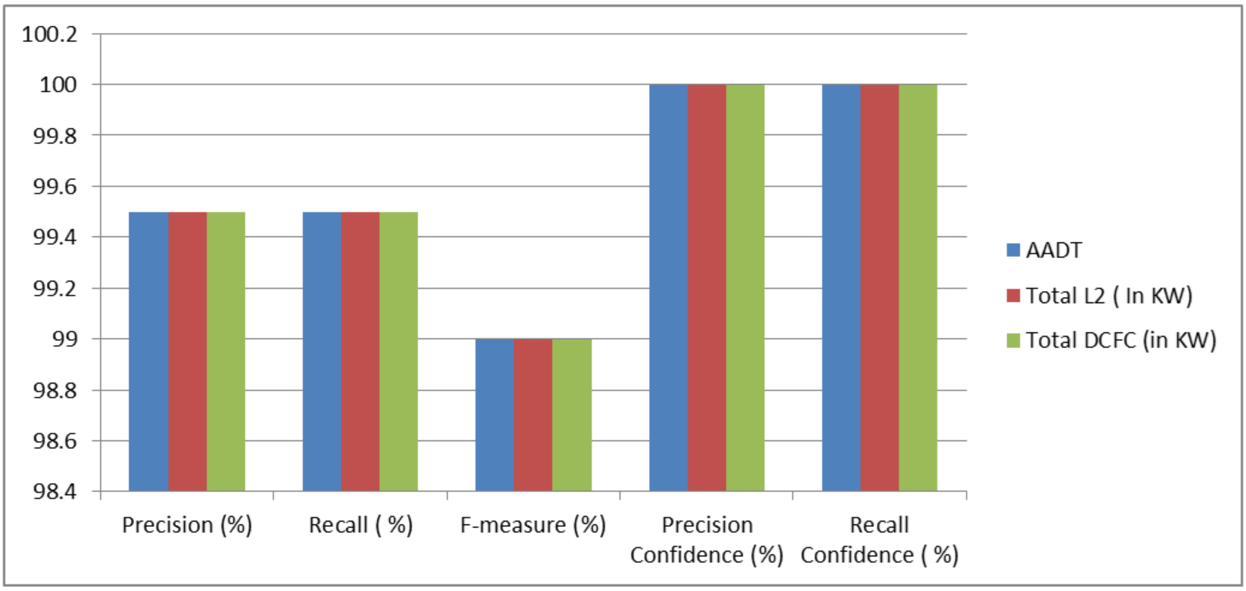

Figure 10: Precision, Recall and F-measure plot

On observing the above graph, we obtained a precision of 99.5%, a recall of 99.5%, an F-measure of 99%, and a precision confidence of 100% and a recall confidence of 100%. These parameters indicate the proposed model provides the best results in prediction of impact on power grids due to EV charging stations.

5. Conclusion and Future Scope

This research article proposes a methodology to predict the impact on power grids due to excessive electrical vehicle charging in and around California state rest areas, using the specific dataset mentioned in the previous steps. The proposed model begins by thoroughly scrutinizing the dataset for missing values using the mice imputation technique, following the preprocessing and labeling phase. The model scrutinizes the dataset to assess the correlation between its attributes using the Pearson correlation estimation model. Additionally, it uses the Shannon information gain to measure the distribution of power factors and identify the most impactful power utility service providers. The obtained data from Shannon's information gain distribution factor is used to split the data based on the given ratio for the training and testing processes. The XGBoost model utilizes the training and testing data for the specified number of epochs and batch size. The trained data thereafter produces the prediction factors for the huge usage of the power for the given service provider. The fuzzy logic model uses these prediction factors to estimate the impact on the service provider and their power grids. We achieved a precision rate of 99.5%, a recall rate of 99.5%, an F-measure of 99%, a precision confidence of 100%, and a recall confidence of 100%. These parameters suggest that the proposed model outperforms others in predicting the impact of EV charging stations on power grids .

To successfully sustain the load on the power system, future study can also evaluate the alternate energy resources that can be harvested and supplied to the charging stations.

References

1. Z. M. Sarkin Adar, A. Alhayd and G. Todeschini, "Predicting EV Charging Duration Using Machine Learning and Charging Transactions at Three Sites," 2024 IEEE International Conference on Industrial Technology (ICIT), Bristol, United Kingdom, 2024, pp. 1-6, doi:

10.1109/ICIT58233.2024.10540858.
2. Gustavo Adolfo Gómez-Ramírez, Rebeca Solis-Ortega, Luis Alberto Ross-Lépiz, Impact of electric vechicles on power transmission grids, Heliyon, Volume 9, Issue 11, 2023, e22253, ISSN 2405-8440, https://doi.org/10.1016/j.heliyon.2023.e22253.
3. Y. Xiong, B. Wang, C. -C. Chu and R. Gadh, "Electric Vehicle Driver Clustering using Statistical Model and Machine Learning," 2018 IEEE Power & Energy Society General Meeting (PESGM), Portland, OR, USA, 2018, pp. 1-5, doi: 10.1109/PESGM.2018.8586132.
4. Aditya Kumar Sharma et al. “AI And ML Innovations in EV Charging: Transforming Smart Grids with Vehicle-To-Grid Technologies”, IJIRMPS Volume 11, Issue 5, September-October 2023.
5. Sichen Li, Weihao Hu, Di Cao, Tomislav Dragičević, Qi Huang, Zhe Chen, and Frede Blaabjerg, “Electric Vehicle Charging Management Based on Deep Reinforcement Learning”, JOURNAL OF MODERN POWER SYSTEMS AND CLEAN ENERGY, VOL. 10, NO. 3, May 2022.
6. Zhou, Dan, Zhonghao Guo, Yuzhe Xie, Yuheng Hu, Da Jiang, Yibin Feng, and Dong Liu. 2022. "Using Bayesian Deep Learning for Electric Vehicle Charging Station Load Forecasting" Energies 15, no. 17: 6195. https://doi.org/10.3390/en15176195.
7. Xinhui Zhao and Guojun Liang, “Optimizing electric vehicle charging schedules and energy management in smart grids using an integrated GA-GRU-RL approach”, Energy Res. 11:1268513. doi: 10.3389/fenrg.2023.1268513.
8. Arif Nur Afandi, Shamsul Aizam Zulkifli, Petr Korba, Felix Rafael Segundo Sevilla, Anik Nur Handayani, Aripriharta, Aji Presetya Wibawa & Farrel Candra Winata Afandi, “Trip Pattern Impact of Electric Vehicles in Optimized Power Production using Orca Algorithm”, J. Eng. Technol. Sci. Vol. 56, No. 4, 2024, 463-473 ISSN: 2337-5779 DOI: 10.5614/j.eng.technol.sci.2024.56.4.3.
9. Noradin Ghadimi et al., “Electric Vehicle Charging Effects on Low Voltage Grids”, International Journal of Optimization in Electrical Engineering, Received 29 February 2018; Received in revised form 21 May 2018; Accepted 02 August 2018.
10. Muddsair sharif, gero lückemeyer, and huseyin seker, “Context Aware-Resource Optimality in Electric Vehicle Smart2Charge Application: A Deep Reinforcement Learning-Based Approach”, Received 16 July 2023, accepted 12 August 2023, date of publication 17 August 2023, date of current version 23 August 2023. Digital Object Identifier 10.1109/ACCESS.2023.3305966.
11. Sakib shahriar, a. r. al-ali, ahmed h. osman, salam dhou, and mais nijim, “Prediction of EV Charging Behavior Using Machine Learning”, Received July 9, 2021, accepted August 3, 2021, date of publication August 6, 2021, date of current version August 16, 2021. Digital Object Identifier 10.1109/ACCESS.2021.3103119.
12. Mostafa M. Shibl, Loay S. Ismail b, Ahmed M. Massoud, “Electric vehicles charging management using deep reinforcement learning considering vehicle-to-grid operation and battery degradation”, Energy Reports, Article history: Received 16 January 2023 Received in revised form 2 May 2023 Accepted 4 July 2023
13. Tehseen Mazhar, Rizwana Naz Asif, Muhammad Amir Malik, Muhammad Asgher Nadeem, Inayatul Haq, Muhammad Iqbal, Muhammad Kamran and Shahzad Ashraf, “Electric Vehicle Charging System in the Smart Grid Using Different Machine Learning Methods”, Sustainability 2023, 15, 2603. https:// doi.org/10.3390/su15032603.
14. Mouaad Boulakhbar, Markos Faragc , Kawtar Benabdelaziz d, Tarik Kousksoua , Malika Zazi, “A

deep learning approach for prediction of electrical vehicle charging stations power demand in regulated electricity markets: The case of Morocco", Cleaner Energy Systems, Received 8 April 2022; Received in revised form 26 September 2022; Accepted 5 November 2022, https://doi.org/10.1016/j.cles.2022.100039.

15. Yanning Lia, and Alan Jenn, "Impact of electric vehicle charging demand on power distribution grid congestion", SUSTAINABILITY SCIENCE PNAS 2024 Vol. 121 No. 18 e2317599121 https://doi.org/10.1073/pnas.2317599121.
16. Kadir Olcay and Nurettin Çetinkaya, "Analysis of the Electric Vehicle Charging Stations Effects on the Electricity Network with Artificial Neural Network", k. Energies 2023, 16, 1282. https://doi.org/10.3390/ en16031282.
17. Paul Eitel and Peter Stolle, "A machine learning approach to model the future distribution of e-mobility and its impact on the power grid", Eitel and Stolle Energy Informatics 2022, 5(Suppl 1):31 https://doi.org/10.1186/s42162-022-00203-w.
18. Saghir Ahmeda, Basit Razaa, Lal Hussainb,c, Amjad Aldweeshd, Abdulfattah Omare, Mohammad Shahbaz Khanf, Elsayed Tag Elding, and Muhammad Amin Nadimh, "The Deep Learning ResNet101 and Ensemble XGBoost Algorithm with Hyperparameters Optimization Accurately Predict the Lung Cancer", Taylor & Francis Group LLC, APPLIED ARTIFICIAL INTELLIGENCE, 2023