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Optimizing Renewable energy harvesting process for EV Charging Stations through machine learning

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Abstract: Due to immense progress in electric vehicles, EV charging stations often suffer from a scarcity of electricity in peak-demanding hours. This is mainly because most of the power grids rely on the technology of hydroelectricity generation, thermal power generation, or nuclear power generation for all our electricity needs, which in turn produces a lot of stress during peak demand hours. To reduce this stress on grids, alternative energy needs to be harvested by analyzing the area of EV charging stations and power grids for the installation of solar panels or windmills. To achieve this, some methodologies exist that use sequential machine learning methodologies to obtain the predicted alternative power harvesting parameters. However, due to the sequential process, all parameters cannot be taken into account for the overall outcome of the recommendations. Hence, this research article proposes an idea of using the hybrid machine learning model to scrutinize the dataset to apply the random forest model to track the environmental changes to identify the possibilities of alternate energy harvesting. The linear regression model uses the tracked parameters to determine the slope and intercept, which in turn yields the prediction parameters for alternate energy. The decision tree model efficiently uses these prediction parameters to suggest alternate energy harvesting parameters, including solar, wind, and other modes.

***Index Terms* - Alternate energy harvesting for EV Charging, Random forest, linear regression, Decision tree.**

I. Introduction

Due to the variable characteristics of electric energy, it often loses a certain quantity until it reaches its destination. This often leads to a significant shortage of electric energy during peak usage periods, such as festivals and EV charging stations. Therefore, alternative energy harvesting has emerged as a crucial technology to address the scarcity of electricity in key locations. These technologies harvest electricity from the natural forces present in nature, preserving the integrity of these natural phenomena. These natural forces include water force, wind speed, solar intensity, wave energy, and many others. Most of the time, EV charging stations consume more electric energy than the stipulated amount due to excess demand in the peak hours. This phenomenon could potentially raise concerns about grid failure or lead to power-down scenarios, which could result in significant economic losses for both the consumers and the county as a whole. Hence, the renewable energy harvesting process has drawn much more importance than ever before. The term "electric car" is most often used to describe vehicles powered by electric batteries. Since petrol is not taxed there, the tax must be derived from either the reported mileage (automatic) or the electricity road charges. The source of the electricity is irrelevant to an electric car, which uses an electric motor to propel the wheels. An electric motor mounted on the rear axle received its power from a dynamo.

There is a 25% reduction in CO_2 emissions from a battery-electric car compared to a gasoline driven vehicle after accounting for material mining, petroleum plastics, manufacturing, and ten years of operation. Since carbon has a direct impact on energy prices, driving an EV will save us 25%.

A hydrogen fuel-cell electric vehicle is significantly less expensive. In a recent report, the Canadian Hydrogen and Fuel Cell Association lauded hydrogen vehicles. Notably, it was mentioned that the carbon footprint is far lower than that of electric vehicles, with 2.7g of carbon dioxide per kilometer compared to 20.9g. A gallon of hydrogen costs $7.52, and a liter costs $2.00. Nevertheless, a business in Canada called Proton Technologies is launching a commercial hydrogen liberation technique that involves flooding oil sands with fire, which traps CO2 underground. The cost drops to $0.10 to $0.50 per liter, or $0.37 to $1.88 per gallon, because the process uses 5% of the hydrogen for energy.

Below, we will go over some important points about the increasing contribution of renewable energy to the development of EV charging networks.

Greening the Power Grid - Electric vehicle charging infrastructure can greatly lessen its impact on the environment by utilizing renewable energy sources such as solar and wind power. Charging electric vehicles using renewable energy makes them a more environmentally friendly option than gas-powered cars.

Efficiency in Cost - Electricity costs can be reduced in the long run by combining renewable energy sources with EV charging stations. One way to reduce reliance on the grid is by installing solar-powered charging stations. These stations produce energy locally.
Free Energy harvesting - charging operators may be sure that they will have more energy independence if they use renewable energy. Even in areas without access to the grid or when power goes out, operators may still provide consistent charging services thanks to their own power generation.

Synergy in Battery Storage - Energy storage systems, especially when combined with renewable energy sources, are crucial for maintaining a steady energy supply and demand. At times when demand is low, these systems can store renewable energy like solar or wind and then use it to charge electric vehicles when demand is high.

Sustainability Goals- A growing number of nations and companies are committing to greater environmental responsibility. Electric vehicles and renewable energy sources work together to achieve these objectives, creating a more sustainable future.

Photovoltaic systems in solar energy design convert the sunlight that falls on panels directly into electricity. This electricity is collected through a series of connections and then supplied to the power grid or transformer, or it can be directly utilized by utility devices such as EV charging stations. Another renewable energy source is wind energy, which involves mounting massive wind turbines in precise locations based on the wind's speed and altitude analysis. Huge blades measuring more than 25 to 30 meters drive these wind turbines, directly converting the kinetic energy of the wind into electric energy upon rotation. The installation of wind turbines relies heavily on factors such as the area, altitude, wind direction, and speed.

Hydroelectricity generation is another clean form of renewable energy where the system is designed to make large volumes of water flow from high altitudes with greater force. The system harnesses this water force to propel a turbine at the base, generating electricity. Most countries use this form of renewable energy, known for its cleanliness, to generate large volumes of electricity. Geothermal renewable energy typically harnesses the earth's natural heat to generate steam, which then powers turbines to generate electricity. This is also considered one of the cleanest forms of renewable energy that we can utilize at the charging stations, depending on their specific locations.

Electric vehicle charging stations near the sea can utilize tidal energy to produce electricity. Here, smart technology harnesses the constant movement of the tides to generate electricity efficiently. Another source of renewable energy is biomass power plants, which ferment organic materials such as cow dung and food waste to produce gases. Generators run on these gases to produce electricity.

[1] A stochastic fuzzy chance-constrained programming model was developed by Tang huiling et al. to control voltage deviation and power loss in distribution systems that include electric vehicles and distributed generation systems. This model successfully reduces power loss and effectively manages voltage deviation. The optimization model of collaborative control of power loss and voltage deviation can be simplified, and optimization problems can be solved more effectively and faster, by transforming the probability density function of uncertainties into the probability distribution function of uncertainties, based on the principle of random fuzzy compatibility. The collaborative control problem of power loss and voltage deviation is solved using a non-dominated sequencing genetic algorithm based on NDC. The result is the Pareto solution set of a multi-objective optimization problem, which helps to control uncertainties and align the decision scheme with decision makers' preferences. When looking into electric vehicles and renewable energy sources, the weather and budget are crucial considerations by [2] Oveis Abedinia et al, Electric vehicle potential planning is critical for intelligent distribution systems. This paper's contribution is a multi-criteria planning of evaluation vehicle based on sustainable resources in an intelligent network; it also aims to limit operational expenditures, calculate the intensity of structure pollution, and remove uncertainty caused by sustainable resources and electronic vehicles in relation to demand response schemes and electric vehicle battery storage structures.

[3] A thorough framework for assessing repurposed EV/PHEV batteries in BESS applications is suggested by Songjian Chai et al. The three parts that make up the framework are: 1) a model for the decline of battery performance; 2) retire modes for electric vehicle and plug-in hybrid electric batteries; and 3) assessment of BESS applications in power systems. One possible solution to the problem of inaccurate load and wind power forecasts is the second-life BESS. The entire cost savings of economic dispatch are maximized across the second life cycle of batteries by optimizing the daily operational energy capacity.

Additional cost savings can be achieved by second-life BESS through reduced service years in vehicle application. Cost savings per megawatt-hour are higher for the BESS constructed from retired PHEV batteries, even though EV battery packs have bigger end-of-life energy capacity and hence produce more cost savings.

To optimize the energy harvesting process at the electric vehicle charging station at the peak hour, the proposed model used a dataset that contains the station location along with its locality and other information. We preprocess this information, maintain it in a double list through imputation and correlation estimation, and then apply the random forest machine learning model to the obtained dataset list. Random forest is known for its complex decision-making ability, which involves creating a number of decision trees to estimate the energy requirements of electric vehicle charging stations. These obtained patterns are then utilized by the linear regression model to measure the slope and intercept so that the model can be used to predict the energy harvesting parameters to maintain the constant flow of the power at EV charging stations.

This research article examines the earlier works of various researchers under the section "Related Work." The "Proposed model" section elaborates on the designed model. The section "Results and Discussion" discusses the obtained results. This research article concludes with potential future enhancements in the last section.

2. LITERATURE SURVEY

[4] Automatic generation control (AGC) with both conventional and distributed sources has been studied and researched by Prateek Sharma et al. for better frequency regulation under various deregulation scenarios and situations. DG units undergo thorough testing under a variety of arbitrary situations, including weather and load fluctuations. We also take into account and study non-linearities such as GDB, GRC, and boiler dynamics in order to conduct a realistic analysis of the AGC framework. The investigated test system has a first-of-its-kind application of the Fuzzy PI and LADRC controller, which has been suggested and executed with great success. To achieve uncontracted demand, which shows interesting and promising results, the suggested AGC system also addresses EVs. To further alleviate the frequency and tie-line power flow instability concern, a demand response mechanism may be used in the proposed system in the future. It is also possible to use another innovative knowledge-based controller to improve the proposed controller. It is possible that the suggested approach, which incorporates FACT devices and may even have an improved controller, could demonstrate a positive effect on the system's performance.

[5] In their study, Sridevi Tirunagari et al. assessed the impact of uncoordinated vehicle-to-grid (V2G) charging and electric vehicle (EV) coordination on power grids. They used simulation case studies to show how unmanaged V2G and EV charging negatively affect power distribution networks. The effects of uncoordinated EV charging on the distribution network's voltage profile, line loading, and imbalance in the network have been shown in simulation case studies. The author then used quasi-dynamic simulations to show how clever coordinated charging works. In instance, the smart charging's efficacy was demonstrated by the flattening of the load profile and the avoidance of undervoltage and overload in distribution feeders. In addition, by facilitating high levels of renewable power penetration, smart charging will also help decarbonize power infrastructure. The results of smart charging trials and studies show that smart charging has several potential monetary, economic, and ecological advantages. The survey also revealed that although some jurisdictions have taken smart charging very seriously through legislative mandates, the vast majority of jurisdictions have not yet adopted or required smart charging for electric vehicles. All parts of the electric vehicle charging ecosystem, including policies and regulatory frameworks, must work together to execute smart charging.

According to Zulfiqar Ahmad Khan et al. [6], one of the smart grid's primary goals is to achieve a balance between electricity generation and consumption. Predictive modeling approaches play a crucial role in efficient management of electricity generation and consumption by coordinating the two to guarantee enough energy transmission to consumers. There are now a number of predictive modeling systems that attempt to foretell future power generation and consumption; however, their practical usefulness is limited due to their high computing complexity and dubious accuracy. With this goal in mind, the author of this work integrated convolutional neural network (CNN) and event-based neural network (ESN) architecture to create a hybrid model for predicting electrical generation and consumption that is both efficient and effective, with reduced running time requirements and high prediction accuracy. The author intends to go further into new technologies like active learning, explainable AI, reinforcement learning, and lifelong learning in the future with the goal of predicting power use and generation.

In a noncooperative distributed control system proposed by Nicola Mignoni et al. [7], an EC offers EVs charging services while taking advantage of the energy storage capacity of nonresident EVs that are parked for an extended period of time. The author has outlined a method for rolling horizon control that uses the ADALM to solve a quadratic optimization model distributedly. The author has demonstrated that this strategy exhibits convergence features in the context under consideration. Numerical experiments using real-world datasets have demonstrated the efficacy of the suggested control technique. In the future, we want to expand the architecture to various energy-sharing and communication contexts and make sure the control framework works properly when unreliable EVs are on the road, since they could send skewed parking distribution parameters to boost their own profits. To conclude, we will investigate the viability and practicality of using the framework to coalitional games to measure the effectiveness of agents' cooperative actions.

An intelligent technique for controlling the voltage of ADNs is suggested by Yangyang Wang et al. [8] using the AWDDQN algorithm. This way, the agent can use the ADN states to intelligently govern the reactive and active power resources, which are customizable. Here are the key takeaways. 1) Resource reactive power can be intelligently coordinated and controlled by the AWDDQN algorithm. 2) Compared to the conventional MINLP methods, the suggested technique is substantially quicker.

[9] Dear Jennie et al., In light of the increasing number of people worried about climate change and pollution, Angela Jose et al. suggested that switching to electric vehicles and using more renewable energy sources to power the grid would be a good way to lessen these negative impacts. The goal of this research is to provide a framework for managing energy consumption in an EVCS-integrated IEEE 33 bus system using a metaheuristic algorithm. We looked at three different renewable energy options: solar photovoltaics, wind farms, and biogas plants. The MAEMS in the SCADA master unit is part of a dynamic pricing plan that aims to reduce the average price that users pay for charging their electric vehicles.

[10] According to Fayez Alanazi et al., who conducted a comprehensive analysis, the idea of connecting renewable energy sources to Riyadh, Saudi Arabia's electric vehicle charging stations (EVCS) is a practical and financially sound one. The city of Riyadh was chosen because of its rapid policy implementation for electric vehicles, its significant contribution to the development of e-mobility, and its abundant renewable energy sources. By utilizing the GPCA for optimal component measurement, this research aimed to lower the TNPC and LCOE while guaranteeing LPSP dependability. More thorough and precise data on electric vehicle (EV) use patterns, charging behavior, infrastructure needs, and renewable energy potential in KSA should be collected in future research to solve these constraints. More accurate modeling and optimization of electric vehicle charging systems would be possible as a consequence, providing stakeholders and legislators with more trustworthy findings and practical insights. Regardless of these obstacles, the study's goal is to provide useful information for policymakers in Riyadh and throughout KSA to encourage the broad use of electric vehicles. Findings from this study can help guide the country's strategic development and execution of electric vehicle charging infrastructure, which is in line with Vision 2030's goals of environmental sustainability and technical advancement. Additionally, the study provides a framework for the best design and implementation of EV charging infrastructure by highlighting existing problems and offering possible solutions. Policymakers and stakeholders in developing nations like KSA can use this framework as a guide to speed up the shift to sustainable transportation systems and increase the number of electric vehicle charging stations.

According to Gabrielle Arena et al. [11], the rapid spread of electric vehicles poses new problems that policymakers, businesses, and academics will have to figure out how to solve. Because of this, this report summarized key findings from the field's study. The present state of electric vehicle (EV) fast charging technology, powertrains, and DC fast charging standards have all been covered in the preceding section. This article has focused on DC networks and microgrids as potential fast charging station designs because to their lower operating costs, lower number of power converters needed, and higher efficiency.

[12] Concerns about the potential negative influence on power systems have been raised by the increasing use of electric vehicles and the incorporation of hydrogen car fleets into transportation networks by Nazmiye Kopacak et al.. On the other hand, this research brings attention to an important facet of good management. It is evident that by effectively managing their charging and refilling operations, these cutting-edge vehicle fleets may improve the reliability of the power grid and reduce the likelihood of problems. The operational expenses and system performance make the implications for model robustness clear. The authors intend to do this in subsequent research by increasing the number of consumption sites for natural gas and broadening the distribution system's restrictions. By doing so, they intend to take into account a more comprehensive set of elements that might influence the distribution and use of hydrogen.

in [13] Electric bus battery switching stations that use photovoltaic (PV) technology were first presented by Terapong Boonraksa et al., who focused on optimizing charging schedules. Charging scheduling made use of metaheuristic algorithms like BBA, WOA, and GWO to minimize energy expenses and peak demand. The results of the simulation showed that energy expenses were reduced by an average of 27.63% and peak load demand was reduced by 23.43%. Energy expenses and PAR were both significantly reduced as a result of the optimization results. You may significantly lower your energy bills by combining a PV power generating equipment with a battery charging schedule. The main points are as follows: • A model for scheduling charging is created for an E-bus battery swapping station that has a fast charging technology. At regular intervals, this model can assess the energy consumption of charging the battery and, using predefined parameters, intelligently choose the best charging period. Crucially, a quick charging method was carefully considered throughout the model's design process. Findings from this study can help utilities and owners of E-bus battery charging stations manage charging in a way that prevents peak demand and keeps the grid stable. A smart city's power system can integrate renewable energy sources more efficiently and save money by smartly scheduling big loads, such as charging stations for electric vehicles. Stakeholders gain from a smart city's energy ecology that is more sustainable and cost-effective thanks to optimized electric bus charging stations. Developing a smart grid system that integrates battery swapping stations with charging schedules and optimizing the E-bus charging system are two areas that will be the subject of future research.

3. RESEARCH METHODOLOGY

The research methodology used to predict the harvesting of the renewable energy at the electric vehicle charging station is depicted in figure 1, and the deployed steps are explained below in detail.

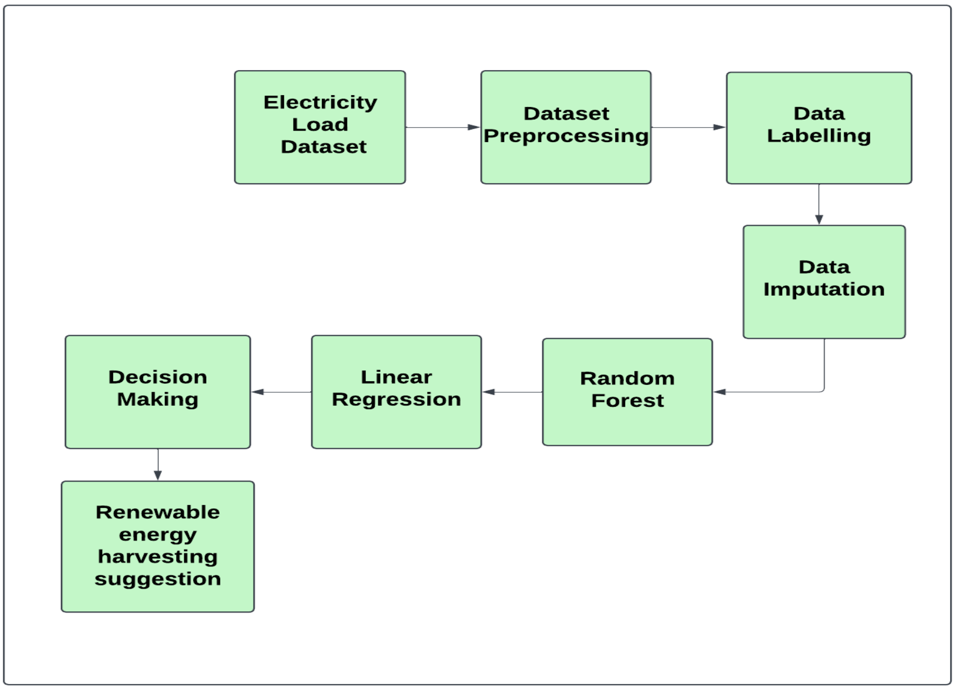


Figure 1: Proposed model methodology

3.1 Dataset collection and processing

To optimize the renewable energy harvesting prediction, the proposed model utilizes the dataset from the URL: https://www.kaggle.com/datasets/pythonafroz/electric-vehicle-charging-impacts-of-r-energy. This dataset contains the details of total power spent on different renewable energy sources. This dataset is stored in the form of a workbook sheet that contains many other subsheets for each of the renewable energy types. For solar energy, the dataset includes attributes such as 'NP15 (MW),' a term that indicates the price of electricity for delivery on a specific date. The 'ZP 26(MW)' attribute indicates the maximum demand for electricity consumption during a specific billing period. The 'SP 15 (MW)' attribute, similar to 'ZP26 (MW),' indicates the highest rate of electricity consumption within a specific timeframe, typically 15 or 30 minutes, along with other attributes such as the total sum (in megawatts). The same attributes are applied to the wind energy dataset worksheet also. The total of these renewable energy is summed up in the other dataset called 'electricity_total'.

This 'electicity_total' dataset contains the many attributes such as 'CALN (MW)' - "Community Alliance for Literacy and Numeracy" (CALN) is all that stands for it. Literacy and numeracy classes are offered by this non-profit organization to adults in the Greater Toronto Area. The Metro West region of Toronto is probably meant to be the one that the organization serves by the MW in CALN (MW). 'SCE(MW)' - The initials SCE (MW) probably stand for Southern California Edison. One of California's most prominent electric providers is Southern California Edison. The number of megawatts (MW) that the acronym SCE (MW) likely stands for is the quantity of power that the business produces. Attribute 'LADWP (MW)' – indicates The Los Angeles Department of Water and Power is known as LADWP, with the abbreviation MW. One of Los Angeles's municipal utilities, LADWP, is responsible for supplying the city with both water and power. Attribute 'SDGE (MW)' – indicates total megawatts of power supplied by the San Diego gas and electric department. Attribute 'IID(MW)' – total megawatt of power supplied by Imperial irrigation District, This is a public agency in California that provides irrigation water and electricity to customers in the Imperial and Coachella valleys. And Final attribute like' sum(MW) is mentioned in the last row of the dataset.

3.2 Dataset Preprocessing

The above mentioned dataset is downloaded in the form of a workbook sheet. The dataset encompasses archives of files detailing solar, wind, and other energy consumption details, as well as various grid consumption details in and around the state of California. We feed the downloaded worksheet paths to the pandas library function, which reads them into the dataset object. We use the obtained dataset object to remove unwanted columns and crop them into the desired shape. To ensure proper data loading in the dataset object, we use the tail and head functions to print the first 5 rows and the last 5 rows, respectively.

We use the describe function to enumerate each attribute for its respective object type, such as integer, float, object, and so on. Following this process, we estimate and enumerate the mean and standard deviation of each attribute, as outlined in equations 1 and 2. Following this process, we describe the minimum, maximum, and each quartile of the column. Additionally, we properly list and depict the histogram of the data for each column, thereby informing the user about the quality of the dataset we are using.

$$\mu = \frac{(\sum_{i=1}^{n} xi)}{n} \quad \text{\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_}(1)$$

$$\delta = \sqrt{\frac{1}{N}} \sum_{i=1}^{n}(xi - \mu)^2 \quad \text{\_\_\_\_\_\_\_\_\_\_\_\_\_\_}(2)$$

Where μ is mean
x_i is Attribute entity
n is the total number of data
δ is the Standard deviation

3.3 Data Imputation

As part of its labeling process, the scikit-learn label encoder in Python examines the preprocessed dataset object to ascertain the data type of each attribute and the object type, which is actually the string type. Following labeling, we numerically transform all data and impute missing values to ensure the dataset is strong and stable. For the purpose of estimating the overall amount and percentage of missing data in each attribute, we construct an oversample object for the dataset. After that, we use fillna() to set each attribute to mode 0, and then the IterativeImputer() iterator gets the entire imputer object. After applying the oversampled object's transformation, the mouse imputer verifies the IQR. By analyzing the effects of mutations, this tool aids in the detection of data outliers. After this, the IQR fills in the dataset's missing values using equations 3, 4, 5, and 6.

Q1=*fxm*(0.25) ____(3)

Q2=*fxm*(0.75) ____(4)

IQR=Q2-Q1 _____(5)

fxm = (*fxm* <(Q1 - 1.5 * IQR) | *fxm* >(Q1 - 1.5 * IQR)) ____(6)

Where

fxm - Mice imputation function

IQR - interquartile range

3.4 Random Forest Classification

We utilize the imputated data from the previous step to identify the pattern of EV charging station location and energy consumption, thereby increasing predictive accuracy and controlling overfitting. To achieve this, a random forest, a meta estimator, employs averaging to train several decision tree classifiers on different sub-samples of the dataset. Forest trees use the optimal split method, which is equivalent to forming the Decision Tree Regressor with the splitter value as the "best" parameter. If If the bootstrap value equals the default Boolean value 'True,' you can control the sub-sample size using the max_samples option. erwise, the creation of each tree utilizes the entire dataset. We use the criteria and the number of trees in the forest as estimators.

We utilize the train_test_split function to divide the maximum number of samples into training and testing phases. We dedicate 85% of the data for training, and the remaining 15% for testing. We set the obtained train and test data lists for the standard scaler class, which standardizes features by removing the mean and scaling the data to the unit variance. We employ the random forest regressor to train the random forest model for the assigned epochs. We use the cross_val_score class to perform the K-fold cross-validation of the random forest model after successful data training. The Random forest regression model schematic diagram can be seen in the figure 2 to get a glimpse of the working of the model.

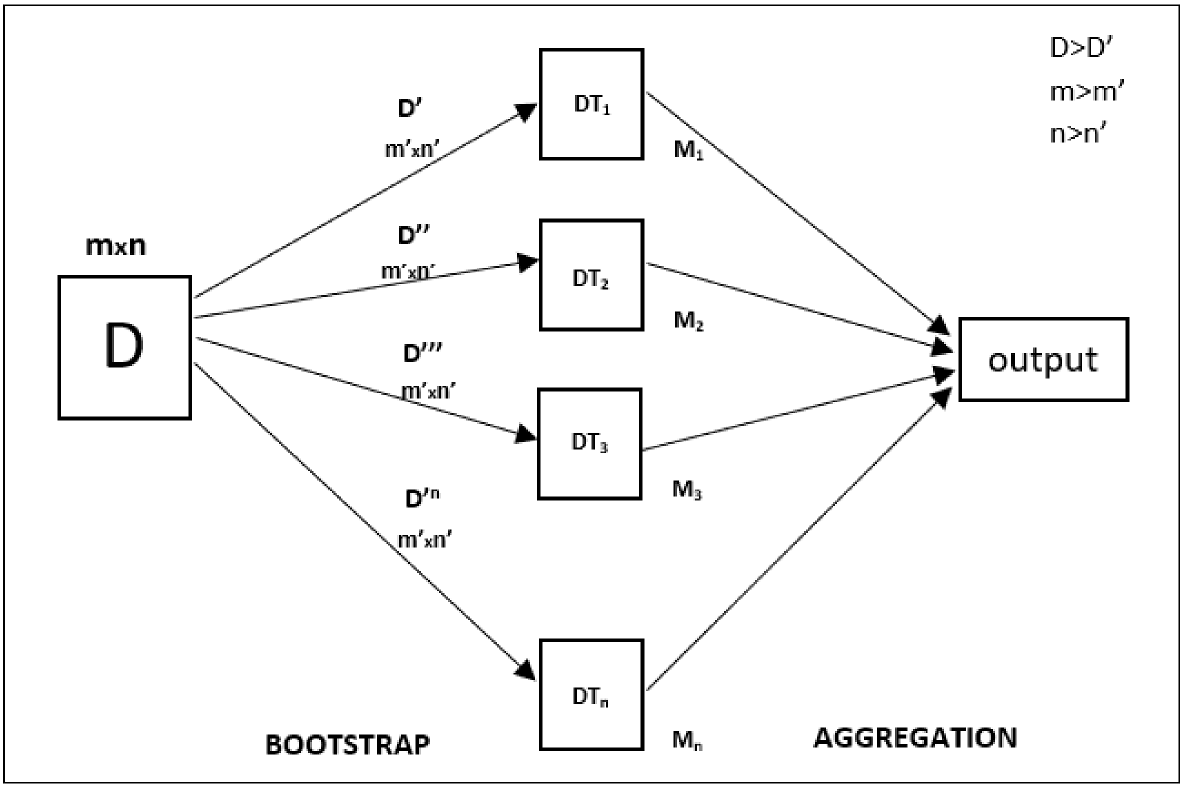


Figure 2: Random forest Regression model

3.5 Linear Regression model and Decision making

The obtained scores from the Random forest model for every type of the renewable energy is stored in the double dimension list with energy type, station location and score as the values. A continuous regression between an independent and a dependent variable is established using the linear regression. We can see these numbers represented in the x [] and y [] lists, where x is the independent variable of Energy type and y is the dependent variable as score. Here is a numerical example of this in equation 7.

Y=MX+B ___(7)

By multiplying the value of b, which represents the intercept, by the undetermined amount of m, which represents the slope, we may obtain the degree of regression using this formula. To get these results, we employ variables like power in Power score W as the dependent variable and Energy type as the independent variable. These parameters are extracted from the initial preprocessed and labeled dataset using equations 8 and 9, and then stored in an array X [] for use in intercept and slope assessment. To input into the equations indicated below, the user-provided values for the field attributes are treated as a Y [] list.

$$M = \frac{\mathrm{N} \sum(xy) - \sum x \sum y}{\mathrm{N} \sum(x^2) - (\sum x)^2} \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_ (8)$$

$$B = \frac{\sum y - M \sum x}{\mathrm{N}} \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_ (9)$$

This is where the independent variable :

Where:
x = Independent variable
y = Dependent variable
M = Slope or Gradient (how steep the line is)
B = the Y Intercept (where the line crosses the Y axis)
N= Size of the array
Y=Intercept value

We can use the evaluated values in equation 7 to determine the value of the dependent variable. We achieve this by factoring in the value the user has entered for a specific property into the system. We supply the values for the independent variable, and then use regression to determine the corresponding y values. This process provides the final scores for the EV charging stations, indicating their potential for switching to the renewable energy mode. The if-then rules use the obtained value of Y from equation 7 to determine the potential level of renewable energy harvesting at a specific EV charging station.

IV. RESULTS AND DISCUSSION

A Windows-based GPU computer with an Intel Core i7 CPU uses the built architecture to predict alternative renewable energy harvesting for charging electric vehicles on the power grid. The machine's main memory is 32 GB, and its secondary memory is 1 TB. The Anaconda repository is used for the Jupyter Notebook and the Spyder IDE.

4.1 Accuracy and loss

As discussed earlier Random forest model is used to train the model to obtain the pattern of the Renewable energy for different EV charging stations. The obtained Accuracy and loss for Random forest model is depicted in figure 3 and 4 below, which is around 81.25% accuracy for the sample epochs of 10.

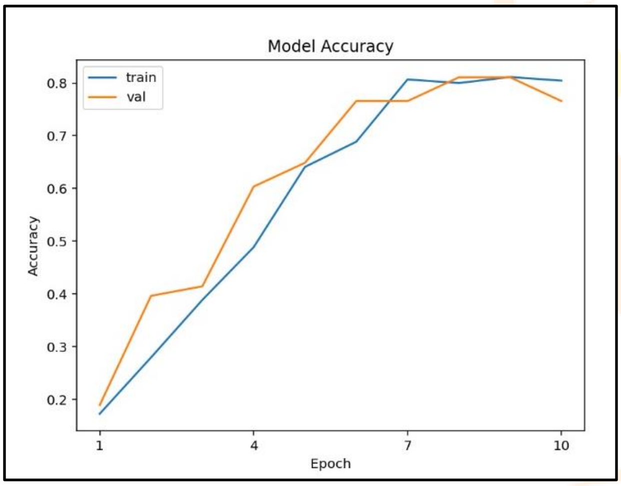


Figure 3: Random Forest model accuracy graph

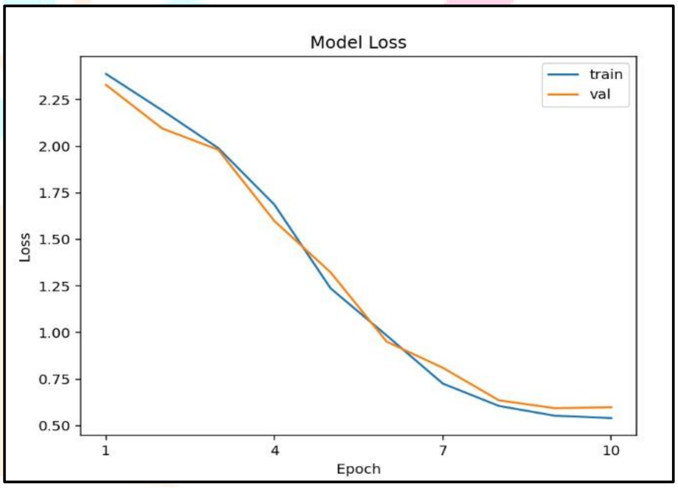


Figure 4: Random Forest model Loss graph

It is evident from the above the graph above that the Random Forest accuracy is getting close to 80% in just 10 epochs and that loss is inversely proportional to accuracy. This proves that Random forest is effective at predicting the effect of Renewable energy harvesting scores.

4.2 Confusion Matrix

Using the given equations as a guide, we evaluated the conducted experiments to determine recall and precision.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad -(10) \qquad \text{Precision(P)} = \frac{TP}{TP+FN} \quad -(11)$$

$$\text{Recall(R)} = \frac{TP}{TP+FP} \quad -(12) \qquad \text{Macro}-\text{F1} = \frac{2*P*R}{P+R} \quad -(13)$$

Where, True positive (TP), true negative (TN), false positive (FP), and false negative (FN) are the four possible outcomes of a forecast. Figures 5, 6, 7, 8, and 9 below shows the resulting graphs for the precision, recall, and F measure.

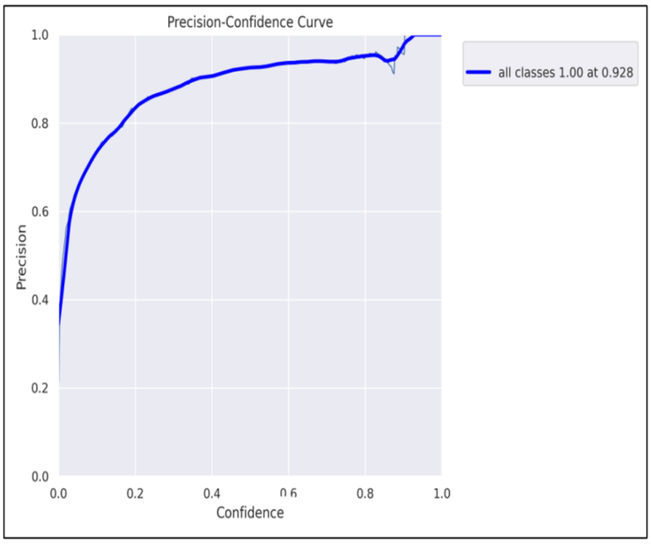


Figure 5: Precision Confidence Graph

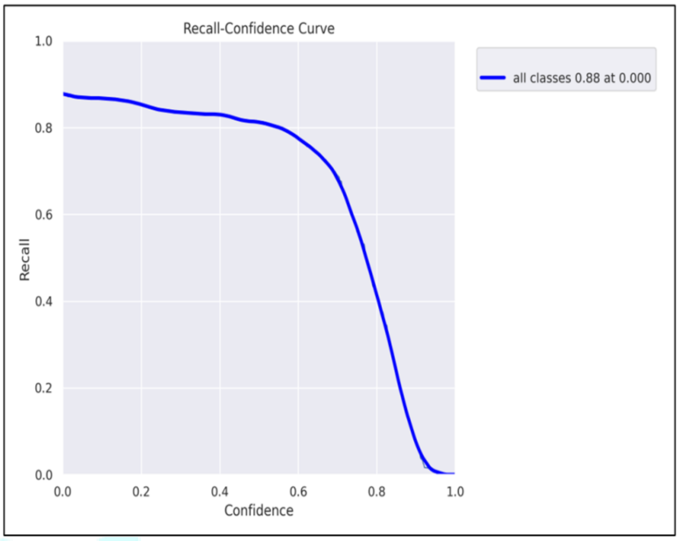
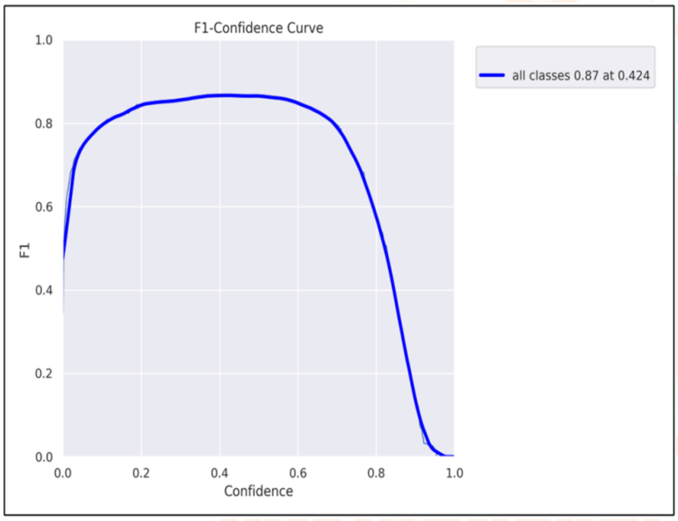


Figure 6: Recall Confidence Graph



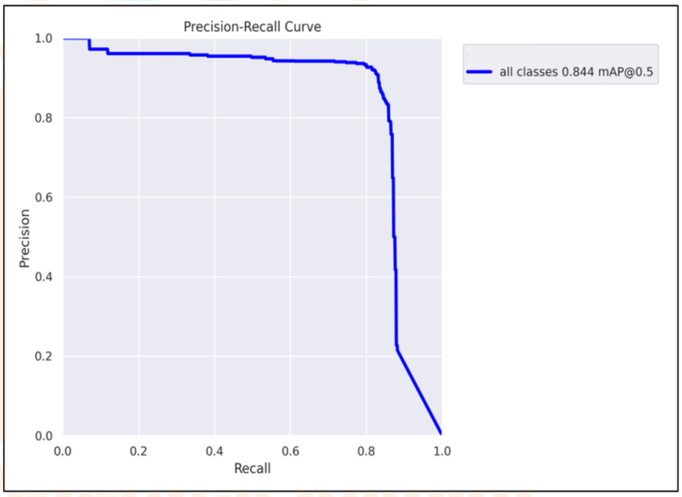


Figure 7: Precision Confidence Graph

Figure 8: Precision - Recall Confidence

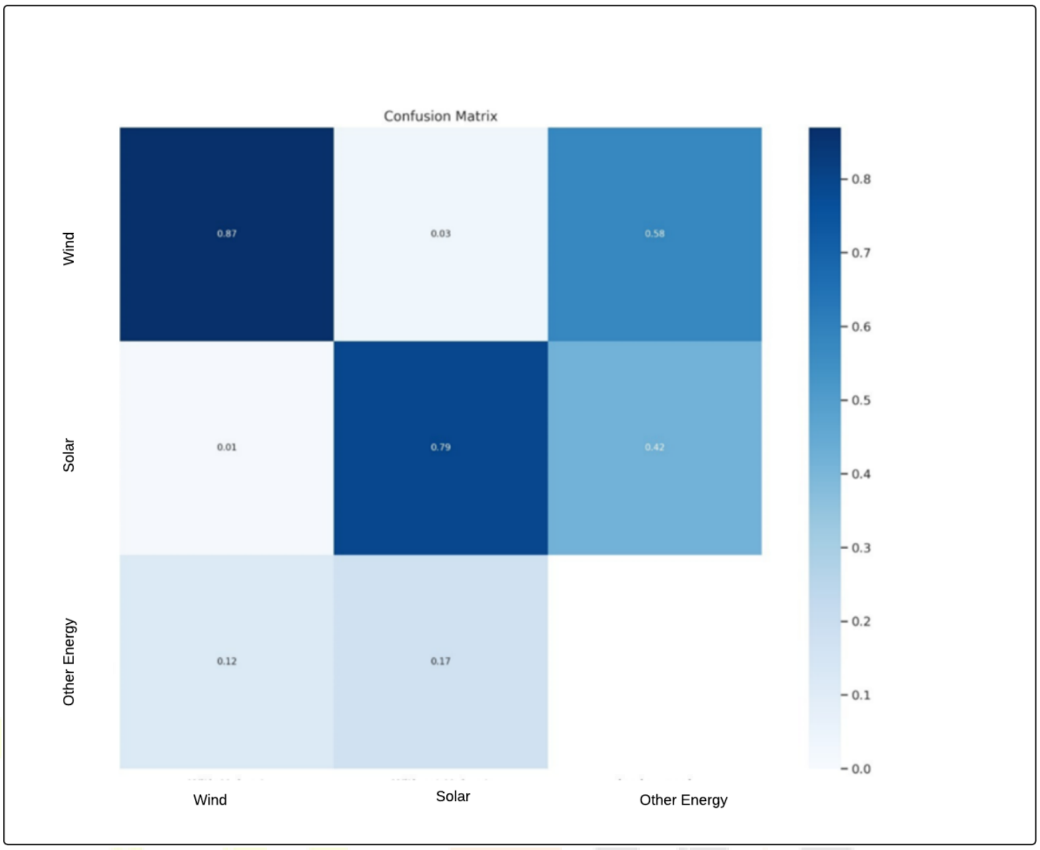


Figure 9: Confusion matrix obtained for the prediction

The model is trained using Random forest for the big dataset for about 200 epochs to obtain the above mentioned precision, Recall and F Measure parameters. This precision and recall is also shown in the below graph in figure 10.

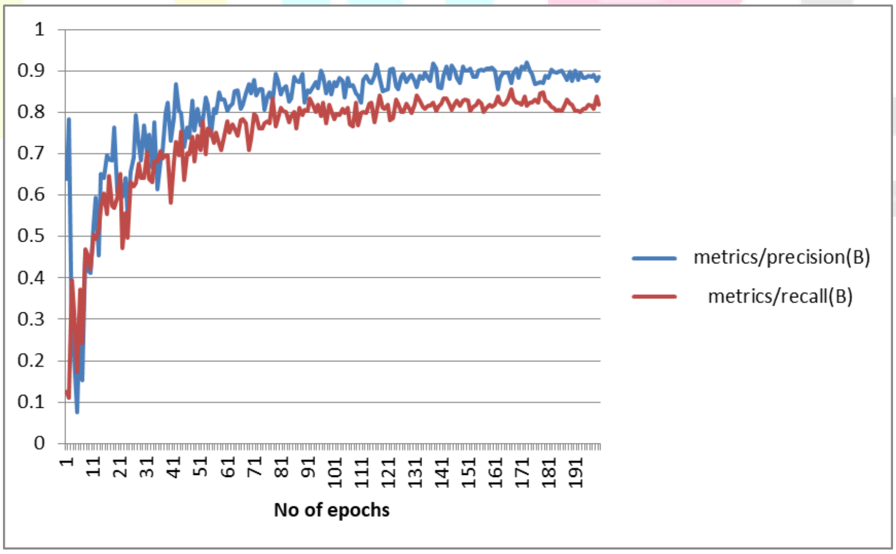


Figure 10: Precision - Recall for 200 epochs

Looking at the graph above, we were able to get an average recall of 74.38% and a precision of 81.24%. According to these metrics, our preliminary research into the feasibility of using the suggested model to forecast aspects related to renewable energy harvesting at electric charging station locations yielded promising findings.

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V CONCLUSION AND FUTURESCOPE

This research paper utilizes the previously mentioned dataset to forecast the demand for renewable energy resources at electric vehicle charging stations located in and around the state of California. This dataset comprises an archive of files containing information on various renewable energy consumption parameters, grid information, and the total power consumption measured in megawatts. Initially, we prepare this dataset for various preprocessing steps such as attribute stripping and imputation. After imputation of the dataset attributes, the proposed model splits the data for testing and training purposes with the ratio of 15:85. The obtained split dataset is used to apply the Random forest model to understand the various energy usage patterns of the charging stations. We apply the linear regression model to the obtained energy consumption patterns by splitting the pattern list into dependent and independent variables. This dependent and independent variable list is utilized to obtain the slope and intercept, and then these values are used to get the prediction score to make the decision to switch renewable energy resources based on the fed dataset attributes. The obtained results clearly indicate that the proposed model obtained a recall of 74.38% and a precision of 81.24%, which are promising results in the first trial of our research.

A future-proof, dependable power supply can be achieved through the optimization of energy storage and the integration of other flexible resources, such as demand-side response programs, as well as through the development of neural network models for the prediction and management of power fluctuations. We can also find the best spots for new renewable energy projects by looking at things like environmental effect, wind speed, and solar irradiance.

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