A study on price predictions for EV Charging Station

A seminar report (Course code: CP301) submitted in partial fulfilment of the requirements for the degree of

Bachelor of Technology

by

Prachi (2020EEB1048)
Vaishnavi Sarah (2020EEB1216)
Priti Shekhawat (2020EEB1194)
Jashandeep Singh (2020EEB1286)
Sakshi Singh (2020EEB1204)
Abhishek Samyal (2020EEB1257)

Under the guidance of

Dr. K. Ramachandra Sekhar

DEPARTMENT OF ELECTRICAL ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY ROPAR

2023

A study on price predictions for EV Charging Station

A seminar report (Course code: CP301) submitted in partial fulfilment of the requirements for the degree of

Bachelor of Technology

by

Prachi (2020EEB1048)
Vaishnavi Sarah (2020EEB1216)
Priti Shekhawat (2020EEB1194)
Jashandeep Singh (2020EEB1286)
Sakshi Singh (2020EEB1204)
Abhishek Samyal (2020EEB1257)

Under the guidance of
Dr. K. Ramachandra Sekhar

K R ch sekhar

DEPARTMENT OF ELECTRICAL ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY ROPAR

2023

Declaration

I certify that this written contribution reflects our views in our own words, with the exception of any places where the ideas and words of others have been used. We have correctly acknowledged and referenced all relevant primary sources. Additionally, we affirm that we followed all rules governing academic honesty and integrity and did not misread, invent, or falsify any notion, data, fact, or source in our contribution. We are aware that any infraction of the aforementioned rules will result in disciplinary action by the Institute and criminal action against the sources who were not properly referenced or from whose permission was not obtained when necessary.

Student Name(Entry Number):Prachi (2020EEB1048)
Vaishnavi Sarah(2020EEB1216)
Priti Shekhawat (2020EEB1194)
Jashandeep Singh (2020EEB1286)
Sakshi Singh (2020EEB1204)
Abhishek Samyal (2020EEB1257)

Date: 27-04-23

Abstract

Electricity from EV charging stations has been the subject of a machine learning-based pricing prediction model. Due to rising EV demand and the ensuing growth in power usage, accurate pricing projection is essential. To anticipate the price of power, the suggested model takes into account a number of factors, including the time of day, the day of the week, the weather, and charging demand. After being trained and tested using historical data, the model's effectiveness is assessed using metrics like MAE and RMSE.

Contents

Abstract **ii**

List of Tables **v**

List of Figures **vi**

1. **Chapter – 1 Introduction** **1**
2. **Chapter - 2 Literature Review** **4**
3. **Chapter - 3**
    - 5.1 Linear Regression model **6**
    - 5.2 Decision Tree model **7**
    - 5.3 Neural Networks **8**
    - 5.4 Support Vector Machine **9**
    - 5.5 Comparison between the Models **10**
    - 5.6 Metrics to Evaluate Model **11**
    - 5.7 Libraries used **12**
4. **Chapter - 4 Methodology** **14**
5. **Chapter - 5 Analysis** **17**
6. **Chapter - 6 Comparison** **31**
7. **Chapter - 7 Conclusion and Future Work**
    1. Future Work **32**
    2. Conclusion **33**
8. **References** **34**

List of Tables

Table 1 - Coamparison between different machine learning models

List of Figures

Levels of EV Charging

Decision Node

Neural Networks

Support Vector Machine

Metrics to evaluate data models

Sample Data sets

Analysis on Datset 1 using ML models

Analysis on Datset 2 using ML models

Analysis on Datset 3 using ML models

Analysis on Datset 4 using ML models

Output of integrated Models

Chapter 1

Introduction

With the world transitioning to a low carbon economy and seeking to mitigate the impact of climate changes, electric vehicles (EVs) are increasingly seen as a promising alternative to reduce greenhouse gas emissions from the automobile and transportation sector. However, the accessibility and availability of a reliable charging infrastructure are essential for the wide-scale adoption of EVs. In this context, the deployment of EV charging stations plays an important role in the transition to electrified transportation.

Electric vehicle (EV) charging stations are the infrastructures that allow electric vehicles to recharge their batteries. The need for charging stations grows with the demand for electric vehicles. These charging stations are available in a variety of settings, including public spaces, parking lots, retail establishments, and private houses. They also come in various forms and power capacities.

There are three main types of EV charging stations: Level 1, Level 2, and Level 3.
Level 1 charger uses standard household outlet and takes upto 20 hours to fully charge the EV.
Level 2 charger provides comparatively faster charging times, and are usually found in public places like shopping centers or office buildings.
Level 3 chargers, or DC fast chargers, are the fastest chargers, and can take as little as 30 minutes to charge the EVs.

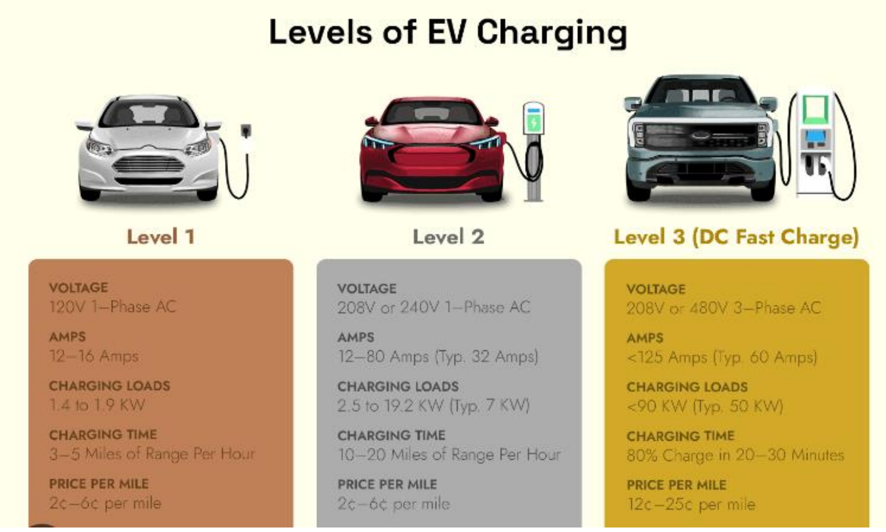


Figure 1.1 Levels of EV Charging

EV charging stations use different charging connectors depending on the vehicle and region type. The European usesType 2 charging stations, while in Japan and some other Asian countries, the CHAdeMO is commonly used for Level 3 charging. In the United States, the most common charging connector is the SAE J1772, which is used for Level 1 and Level 2 charging.

EV charging stations utilization offers a more environmentally responsible form of transportation which is one of the main advantages for the future world. EVs generate no carbon emissions, making them a more environmentally friendly approach rather than the usual fuels. Also, EV charging stations provide great comfort to the users as they can recharge anywhere without any hustle.

The demand for EVs is growing day by day, so is the need for reliable infrastructure for these EVs. But if we further look into it then the cost of charging an EV depends on two most important factors which are first the location and the second the natural resources.To nullify these issues, our project aims to develop a charging calculator that helps EV owners to calculate the cost of charging their vehicles at the solar-powered EV charging stations.

Our charging calculator includes many factors such as the battery capacity, the type of EV used, the current state of charge,etc to provide a near to accurate cost of charging. Alsothe primary source of power for our charging stations is the solar energy with grid energy used only as a backup. This method helps in reducing the carbon footprint as well as the cost.

We shall analyze the reliability of the solar-powered energy source, the usage patterns of the charging stations and the accuracy of the calculator. Also we will identify the barriers that led to the deployment of these EV stations so that the problems can be tackled.

As our main aim is to promote the adoption of EV’s and contribute to the sustainable development of the world, so through our initiative of promoting the development of solar powered charging stations we hope to make a change.

Chapter 2

Literature Review

EVs are gaining popularity as a low carbon emission product and this is increasing its demand. As more Evs start to run on road we need to come up with an infrastructure for this.

One such approach is the utilization of renewable energy sources, like solar power, to operate EV charging stations. EV charging stations powered by solar energy provide several benefits compared to grid-powered stations. Firstly, they rely on renewable energy, which causes no air pollutants during operation, thereby reducing carbon emissions. Also they help in cost reduction for EV owners as they rely on free energy from the sun.

The viability and efficiency of solar-powered EV charging stations have been evaluated in a number of studies. The effectiveness of a solar-powered EV charging station was studied in China in 2020. The study found that, with extra solar energy being supplied back into the grid, the station was capable of meeting the charging needs of EVs during the day. However, weather conditions such as cloudy days impacted the station's performance, leading to lower charging capacity.

In 2020, Zhang assessed the US's viability of solar-powered EV charging stations. The study reports that depending on the size and location of the station, solar-powered charging stations might save up to 40% of the cost of grid-powered stations. The authors highlighted that the initial expense of setting up solar panels and storage batteries might prevent the widespread use of solar-powered charging infrastructure.

Renewable energy sources, including wind power and geothermal energy, have also been evaluated as possible energy sources for EV charging stations. For instance, Yoo et al. in 2019 studied a wind-powered EV charging station in South Korea. The study reports that the station has the potential to reduce greenhouse gas emissions by up to 30% when compared to grid-powered stations while also offering stable and affordable charging.

Chapter-3

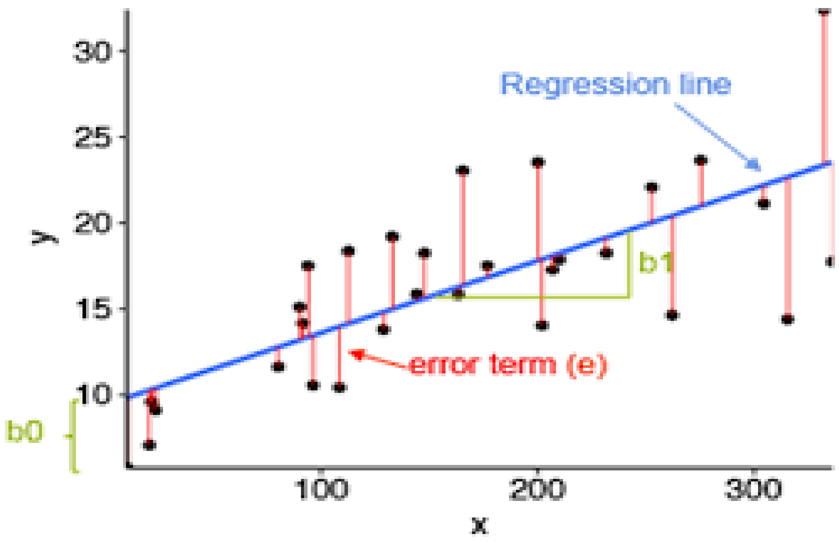
3.1 Linear regression model

Linear regression is a method to predict output from input by defining a linear relationship between input and output variables.

1.1. Linear regression is a method to predict output from input by defining a linear relationship between input and output variables.

1.2. Simple linear regression has only one independent variable and is the simplest regression model.

1.3. Its goal is to find the suitable line so that less error will come and the model best fits the actual results.



3.2 Decision Tree Model

3.2.1 It is a common machine learning algorithm which can be used for both regression as well as classification algorithms.

3.2.2 The decision node predict the maximum seperability between the data and is find by calculating information gain.

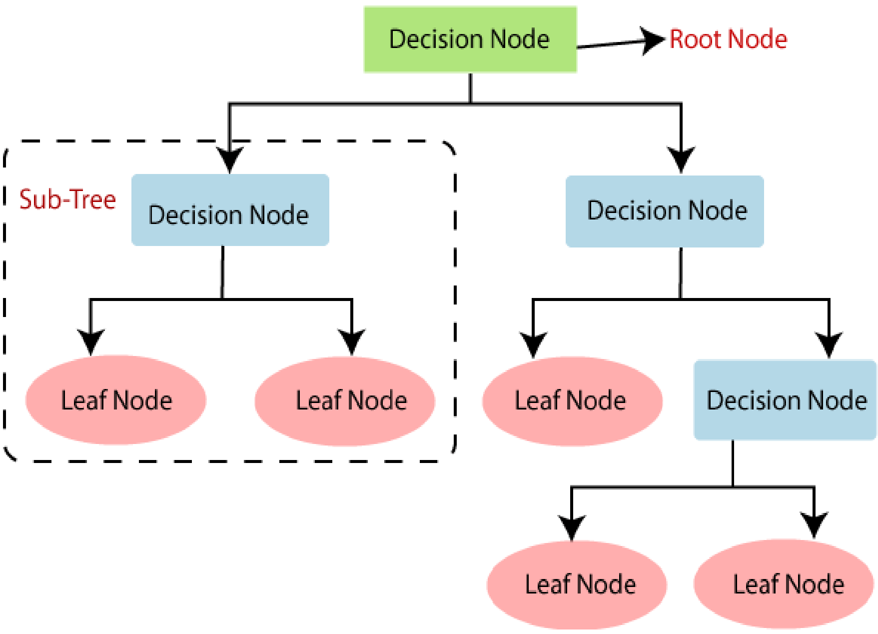


Figure 3.1 Decision Node

3.3 Neural Networks:

3.1 Neural networks is a machine learning model which is inspired by the structure of the human brain. It consists of nodes called neurons.

3.2 It consists of input layer , output layer and the hidden layer and uses the backpropagation method to update the coefficients of nodes.

3.3 Connections between different layers are weighted and are updated by backpropagation method.

3.4 It can solve various problems of machine learning but the time complexity is high

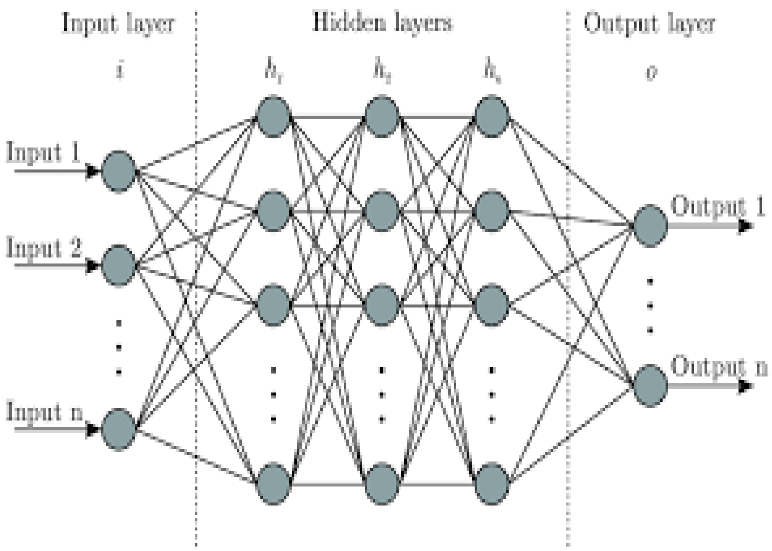


Figure 3 Neural Networks

3.4 Support vector machine:

3.4.1 SVM is a model used for both classification and regression models. It works by finding a hyper plan which is called boundary to separate two different classes.

3.4.2 In the Classification problem, it tries to find a hyperplane that maximizes the distance between the two classes. SVM finds the hyperplane that maximizes this margin and thus helps in reducing the overfitting problem.

3.4.3 If the input is not linearly separable then SVM uses the algorithm called a kernel which is used by shifting the data to another dimension.

3.4.4 In regression analysis, when a continuous value is to be predicted rather than a discrete class, SVMs can be used.. In this case, the SVM searches for a hyperplane that minimizes the sum of the distances between the hyperplane and the data points.

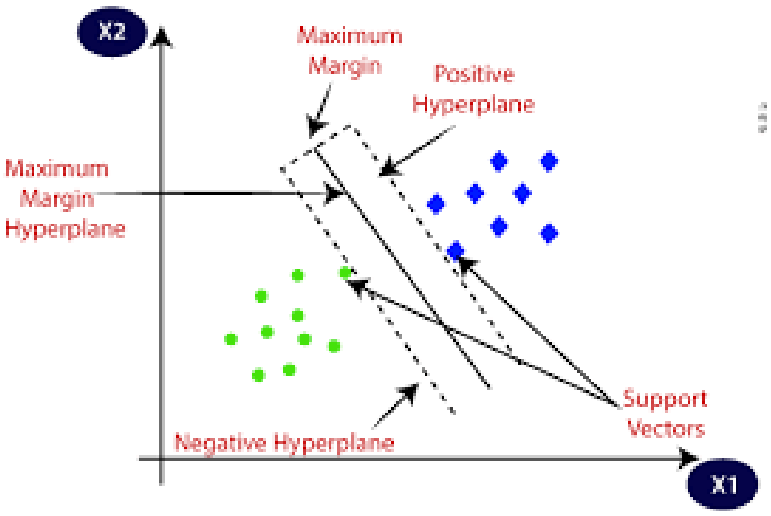


Figure 4 Support Vector Machine

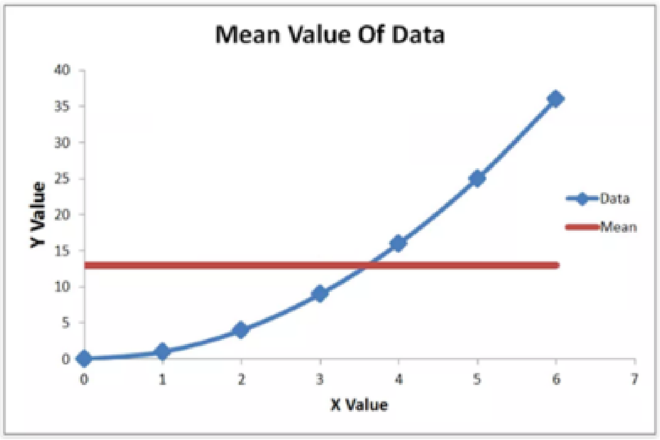
3.5 Comparison between the models:

Models/ Properties	**Linear regression**	**Decision tree**	**Neural networks**	**Support vector machine**
complexity	linear regression is considered as relatively simple and straightforward statistical technique	Decision trees are quite complex and difficult when levels increase.	Neural networks are more complex	complexity depends on several factors such as the dataset size, kernel type, kernel parameters, regularization, and margin size.
flexibility	Linear regression is a simple and flexible algorithm	Its is a non-parametric model and is flexible algorithm	It is highly flexible and can model complex nonlinear relationships between variables.	It is flexible models which can handle both linear and nonlinear data.
Interpretability	The interpretation is straightforward	Decision trees are also interpretable models,	It is generally less interpretable than linear regression or decision trees, as the complex nonlinear relationships	SVM are also less interpretable than linear regression or decision trees
training	Simple algorithm that can be train easily,	Relatively fast to train	Computationally expensive to train	Training time depends on data sets.

3.6 Metrics to Evaluate Model

3.6.1 R-squared

R squared is defined as how good our linear regression line is from the simplest horizontal mean line.



$$R^2 = 1 - \frac{\text{SSE}}{SS_{Total}}$$

3.6.2 Root mean squared error(RMSE) and mean square error(MSE)

a) RMSA is the measure of goodness to fit.

b) MSE can be calculated as the sum of squares of all prediction errors Root Mean Square Error.

c) RMSE is defined as the square root of MSE.

d) It gives an absolute number on how much our model predicted results deviate from the ground truth.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2}$$

Where,

$\hat{y}$ $-$ *predicted value of y*
$\bar{y} -$ *mean value of y*

3.7 Libraries Used:

3.7.1 NumPy: It is a well known Python library that offers a variety of tools for working with arrays and including linear algebraic equations, mathematical function and random number generators.

3.7.2 Pandas: Data manipulation and analysis is obtained using this well known python library. It provides tools for managing structured data such as data frames as well as writing various data formats like excel files and CSV.

3.7.3 Scikit-learn (or sklearn): Scikit-learn is a ML library for Python. It provides so many tools for ML tasks, such as regression, classification, clustering,etc.

3.7.4 train_test_split: train_test_split is from the scikit-learn library which is used to split a dataset into training and testing sets.

3.7.5 Decision Tree Regressor: It comes under the category of decision tree branch which involves regression and classification and it is used to solve regression problems. For example, prediction of how many people will die because of accident.

3.7.6 TensorFlow: It is an ML library made by the multinational company, Google. It provides a flexible and scalable platform for building various ML models.

3.7.7 Standard Scaler: It is a data pre-processing technique that is used to standardize the scale of the input features. It scales each feature to have a mean of 0 and a standard deviation of 1.

3.7.8 Dense and Dropout: These are two types of layers used in neural networks. Dense layers are fully connected layers, where each neuron is connected to every next neuron in the previous layer. Dropout layers randomly drop out some of the neurons during training, which can help prevent overfitting.

Chapter-4

Methodology

Our study involved the use of five different datasets to develop a charging calculator for electric vehicle (EV) users. The datasets we used are as follows:

1. **Solar irradiance data:** The amount of solar radiation that reaches the research area in various weather situations is disclosed in this dataset. We projected the quantity of solar energy that the charging stations could capture using this data. We did this by utilising four different machine learning models: support vector machine, decision tree, neural networks, and linear regression. We utilised these models to forecast how much solar energy will be captured at any given time under various weather circumstances by training them on the solar irradiance data.

2. **Radiation vs cost data:** Based on the amount of solar radiation available, we utilised the four machine learning models from the first dataset to forecast the cost of electricity. The cost of electricity and sun radiation are inversely related. We used this information to forecast how much power generated by the solar panels would cost at any given time.

3. **Grid power cost data:** To create a dataset for predicting power costs for grid electricity, we used the same four machine learning models from the previous dataset. This dataset demonstrated a direct correlation between grid power consumption and price. We made predictions about the cost of power that would be drawn from the grid at any given time using this data.

4. **Solar vs grid power data:** Based on the amount of solar radiation present at the moment, we separated the demand for energy into two categories: power generated from solar and power sourced from the grid. The quantity of solar energy that would be gathered at any given moment was calculated using the expected solar radiation

from dataset 1. The amount of the demand that solar power could satisfy was calculated by comparing this figure to the demand for electricity at the time. Power from the grid was used to supply the remaining portion of the demand.

5. **Integrated dataset:** To create a charging calculator for EV consumers, we combined all the prior datasets. We begin by entering the necessary information, such as the location, time, and type of vehicle. The amount of solar radiation that would be present at the specified location and time was forecast using the machine learning models from dataset 1. The power source was then divided based on demand and the amount of solar radiation available using the dataset for solar vs. grid electricity (dataset 4). Then, to estimate the cost of power generated by solar energy, we used the radiation vs. cost dataset (dataset 2). The cost of power sourced from the grid was finally predicted using the dataset for grid power costs (dataset 3). Adding both costs yielded the final price.

Utilising Python programming, we built a pricing calculator based on the final integrated dataset. The charging calculator asks EV owners to input their location, the time of day, and the type of car they have to know how much it will cost to charge their vehicle. The amount of solar radiation expected to be present at that time and location and the cost of grid-supplied energy are the two main factors used to determine this estimate.

Chapter-5

Analysis

Dataset - 1: Predicting the solar radiations per unit area depending on the weather conditions at that point of time

Input - Temperature, Humidity, Cloud Cover and Wind Speed

Output - Solar Radiations per unit area

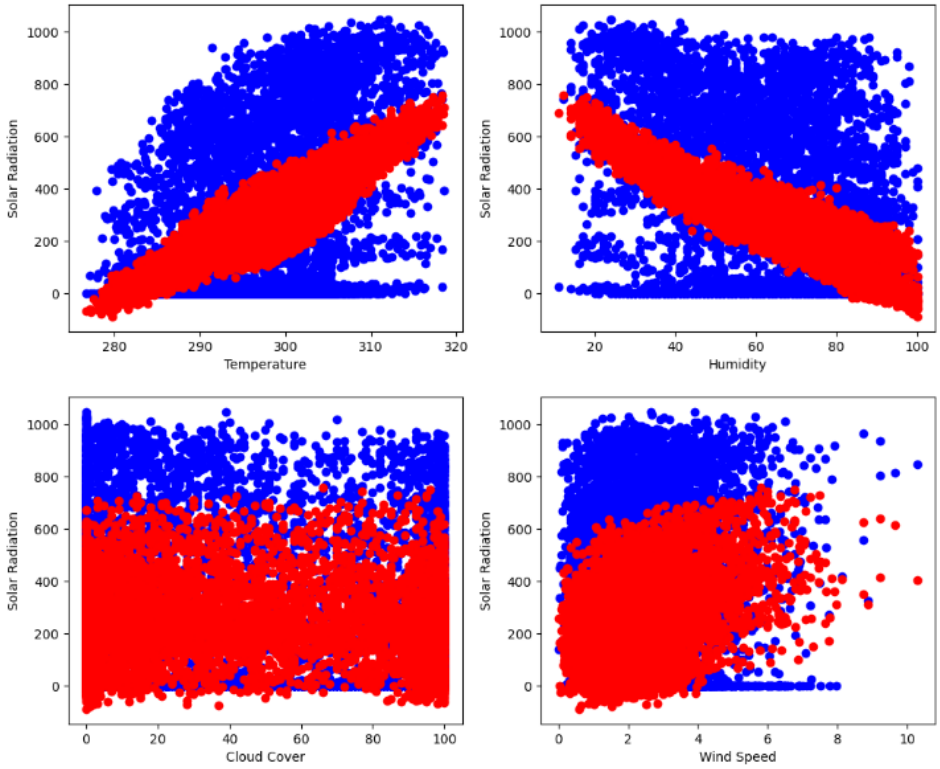
The data set has been taken from previous studies. Sample dataset looks like:

```
temp,humidity,cloud_cover,wind_speed,solar_radiation
278.52,98,0.0,3.21,0.0
278.43,99,0.0,3.23,0.0
278.4,97,8.0,2.89,62.48
277.49,96,6.0,3.02,230.52
277.94,92,3.0,2.73,391.83
285.14,71,3.0,3.0,510.15
287.69,61,0.0,3.53,580.5
288.03,56,11.0,3.94,575.1
289.47,49,17.0,4.06,505.45
290.34,45,17.0,3.97,378.95
288.23,51,31.0,4.0,214.3
287.67,55,49.0,3.13,50.15
286.26,61,54.0,2.6,0.0
285.71,65,34.0,2.38,0.0
283.89,72,31.0,2.38,0.0
```

Now, we train our models based on this data. We found the using each model and analyse them graphically. Then, decided upon which model is best.

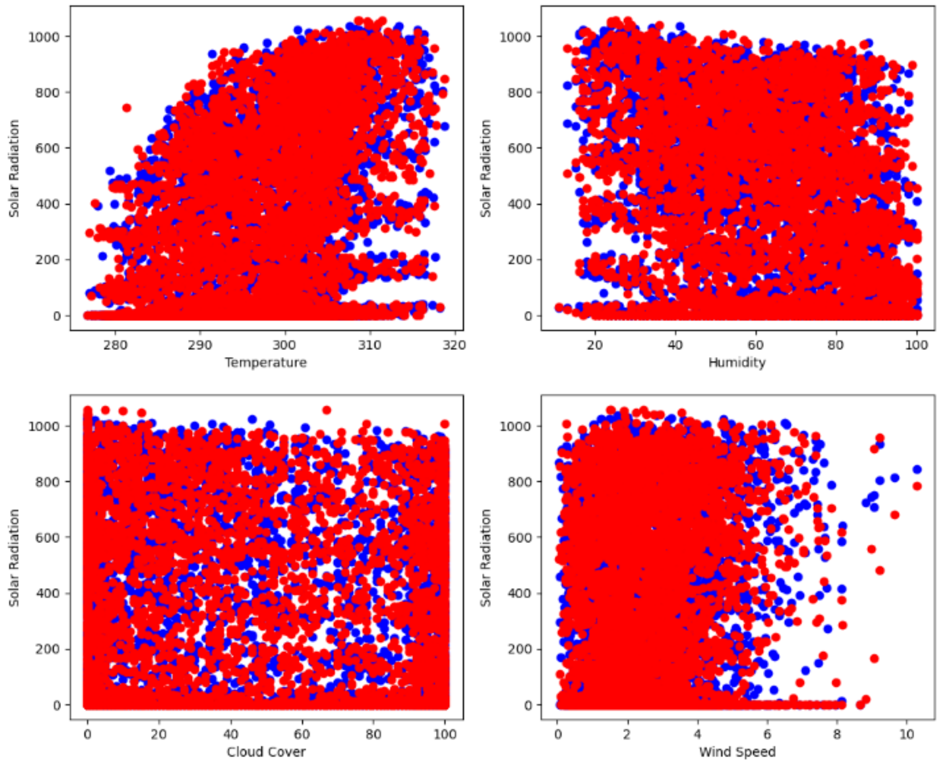
i) Model 1 - Linear regression

```
RMSE: 282.9434951913996
Mean squared error: 80057.02
R-squared: 0.23
```



ii) Model 2 - Decision Tree

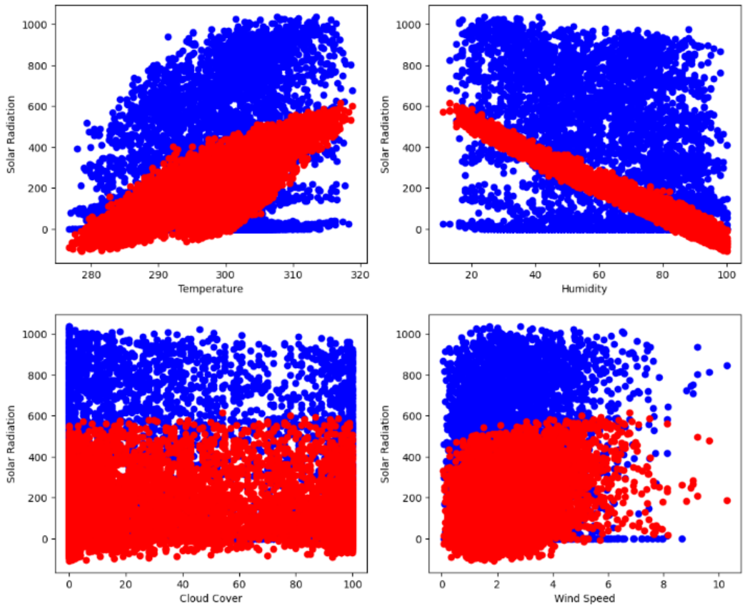
```
RMSE: 358.96239972543367
R-squared score: -0.25
```



iii) Model 3 - SVM

RMSE: 297.5857330318756

R-squared score: 0.13886715654597637

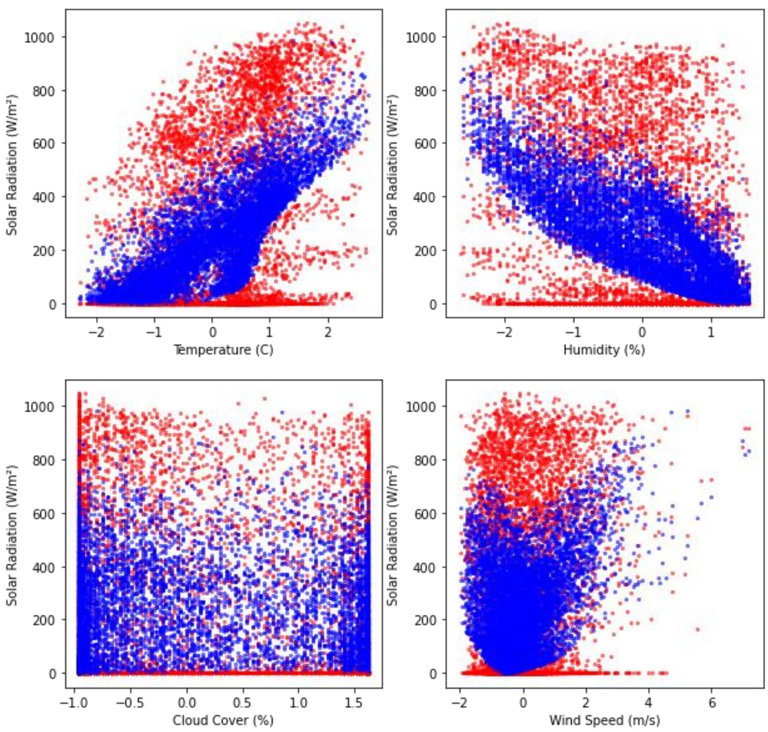


iv) Model 4 - Neural Networks

Mean Squared Error: 72555.01

Mean Absolute Error: 215.82

Actual vs. Predicted Solar Radiation



Based on the RMSE errors, we may conclude that neural networks were the most effective. SVM runs the slowest while Linear Regression runs the fastest in terms of time. On the basis of the graph, we can see that although neural networks disperse predicted values throughout the real dataset and decision trees entirely overlap predicted and actual results, linear regression and svm align predicted data in a linear fashion at the middle of the actual dataset.

Dataset - 2: Predicting the cost of solar radiations

Input - Solar Radiations

Output - Cost per unit area

As some actual data wasn't present so we designed the dataset ourselves. We followed the inverse relation here, that is, as the radiations increases, its cost decreases. We found the mean of all the radiations present and assigned a reference cost to it. For this case, our mean value of radiation data is 4870.44 and reference cost for this much radiations is Rs.6. Then we followed the following equation for calculation cost at different radiation amount.

$$\text{Cost} = \frac{Mean\ radiations * Reference\ Cost}{New\ Radiation} = \frac{480.944 * 6}{x}$$

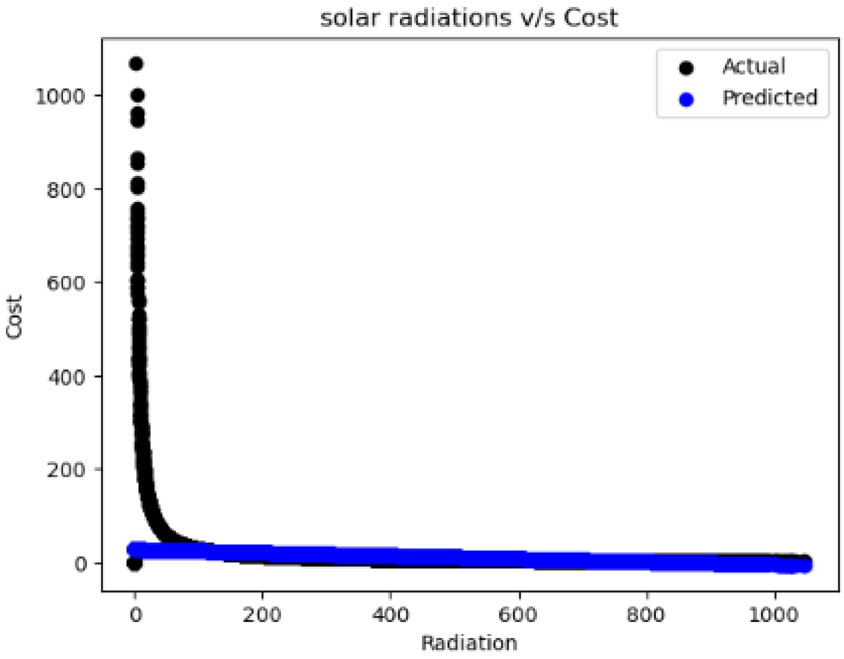
But, a slight change was made. When the radiations were zero, we didn't follow this relation as the cost will tend to infinity. We assigned zero cost of solar power if we had no radiations.

Sample dataset looks like:

```
Radiation,Cost
0,0
0,0
62.48,46.1854
230.52,12.51806
391.83,7.364581
510.15,5.656501
580.5,4.970997
575.1,5.017673
505.45,5.709098
378.95,7.614893
214.3,13.46553
50.15,57.54065
0,0
```

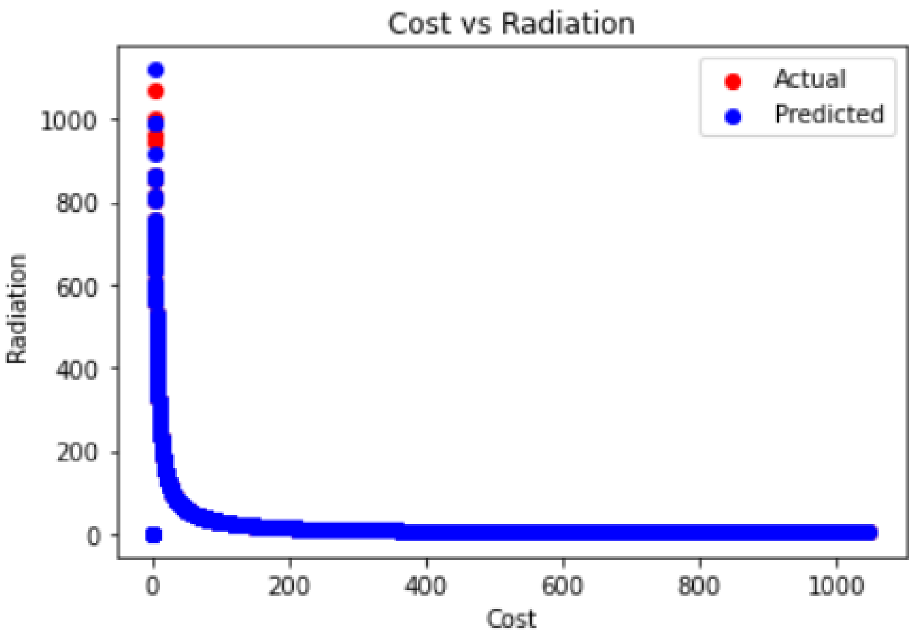
i) Model 1 - Linear regression

```
RMSE: 65.6906123732107
Mean squared error: 4315.26
R-squared: 0.01
```



ii) Model 2 - Decision Tree

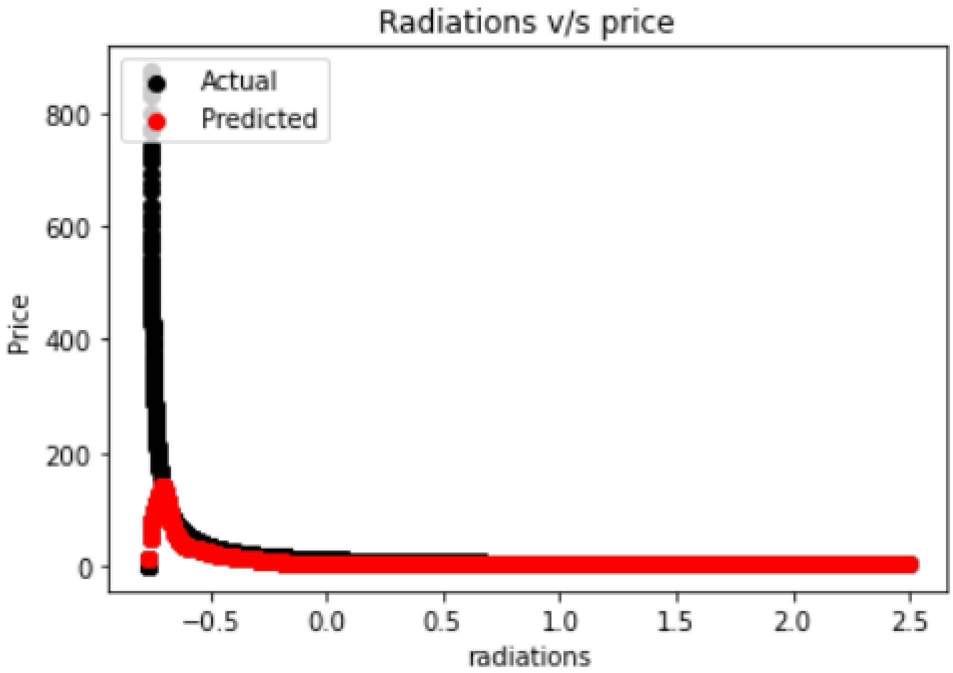
```
RMSE: 0.7638829221525513
R-squared score: 1.00
```



iii) Model 3 - Neural Networks

Mean Squared Error: 2934.32

Mean Absolute Error: 14.29



We ran the SVM model but it took so long to run and hence was not efficient. Based on RMSE error values, we conclude that decision tree is the best choice. On the basis of time, SVM takes the longest time to run and then neural networks but Linear Regression is the fastest. Also in graphs, because of our assumption of taking zero cost at zero radiations and not following our equation, we can see a deviation in actual and predicted values around zero values. But the graphs converges at later stage.

Dataset 3:

Predicting the cost of power taken from power grid.

Input - Units required from grid

Output - Total price of gride power

As some actual data wasn't present so we designed the dataset ourselves. We followed the direct dependence relation here, that is, price of grid power increases as as our consumption increases. Also, for different consumption ranges, our per unit cost also changes. This is as follows:

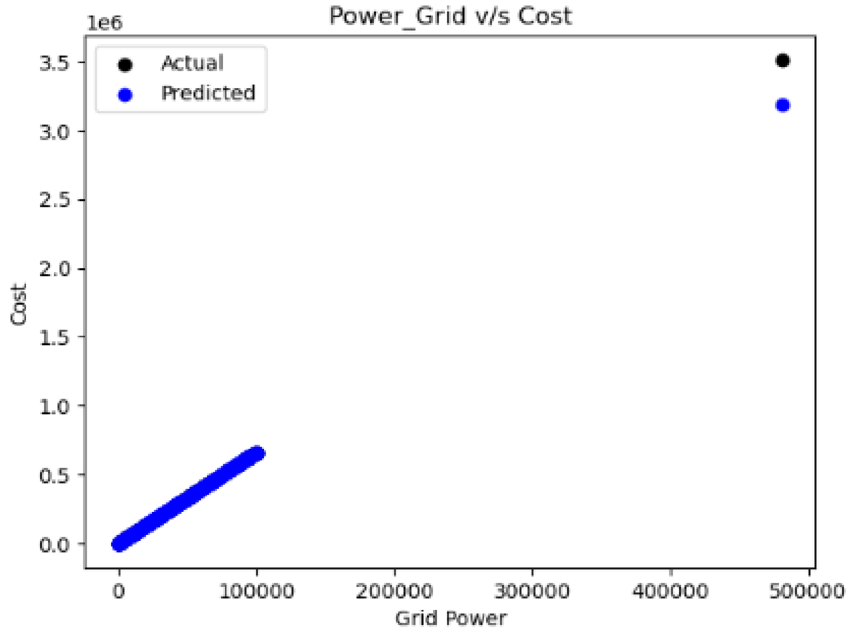
For 1-1000 units, cost per unit is Rs. 5.84 . For 1000-100000 units, cost per unit is Rs. 6.63 . For 100000-500000 units, cost per unit is Rs. 7.3 and for 500000-1000000 units, cost per unit is Rs. 7.5 .

Once we have the required power from grid, we can select the range and multiply the consumption with price per unit to get the total cost of grid power. In this way, we generated this dataset. Tha sample dataset is shown:

```
Power_Grid,Cost
481060.459,3511741.351
1515.970638,10050.88533
70116.98643,464875.6201
25077.54573,166264.1282
1381.600309,9160.01005
46015.37009,305081.9037
94238.92798,624804.0925
97178.60523,644294.1527
28881.51074,191484.4162
20027.26948,132780.7967
3953.378589,26210.90005
93028.83982,616781.208
32632.33326,216352.3695
72073.1451,477844.952
```

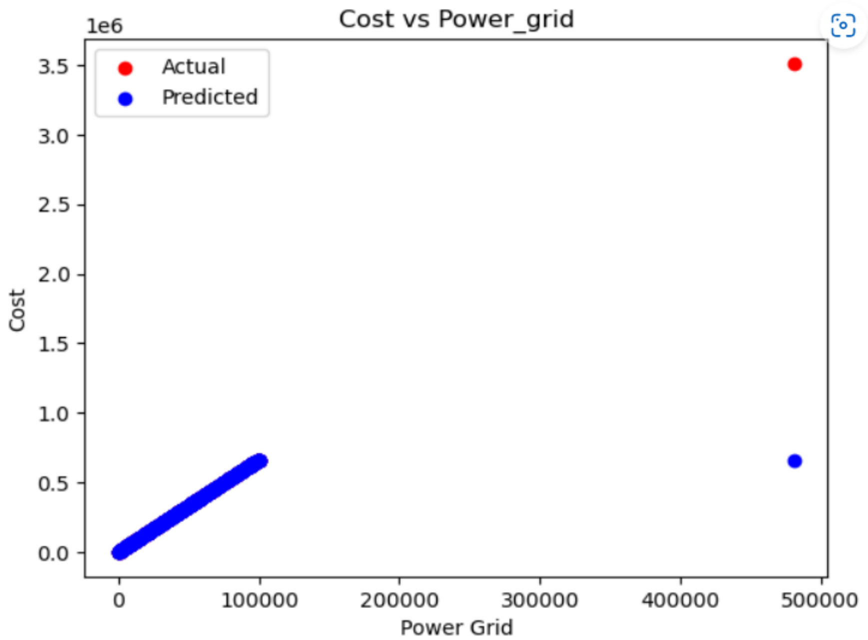
i) Model 1 - Linear regression

```
RMSE: 12787.262425558818
Mean squared error: 163514080.34
R-squared: 1.00
```



ii) Model 2 - Decision Tree

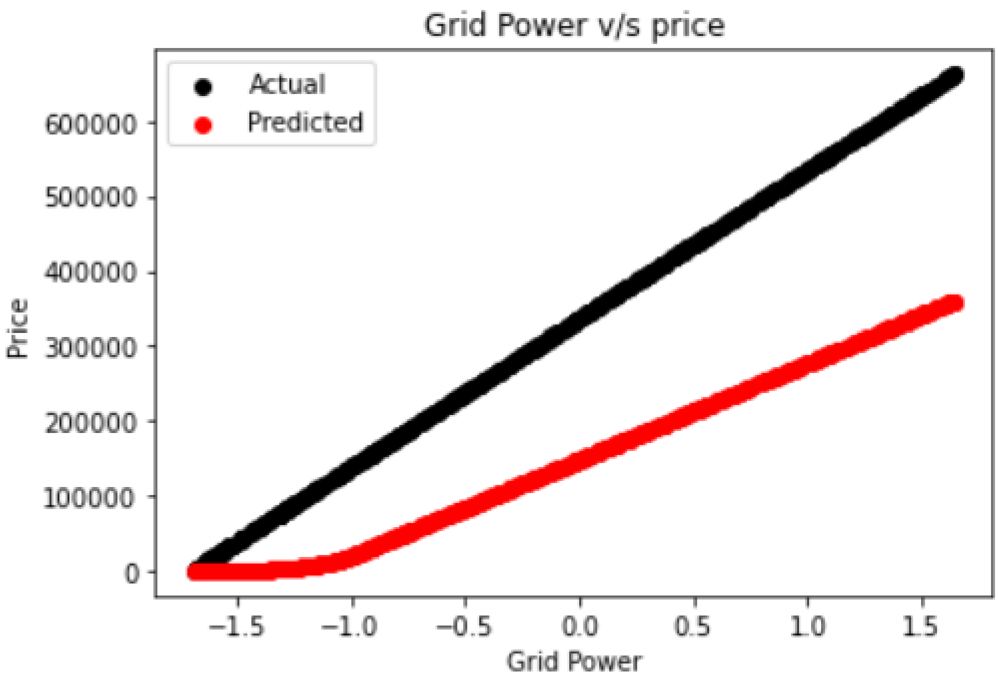
```
RMSE: 113053.77691383973
R-squared score: 0.76
```



iii) Model 3 - Neural Networks

Mean Squared Error: 36556247040.00

Mean Absolute Error: 174562.89



We ran the SVM model but it took so long to run and hence was not efficient. Based on RMSE error values, we conclude that linear regression is the best choice. On the basis of time, SVM takes the longest time to run and then neural networks but Linear Regression is the fastest. On the basis of graph, one important observation we made was regarding some mismatched values in data set. Though the actual and predicted values were closely matching in the initial stage but still we are having a large error. This is because of the some error data values at the end of data range where actual and predicted values are so different and hence a large error and deviation from desired behaviour.

Dataset - 4:

Dividing user demand into power taken from solar panels and power taken from grid on the basis of solar radiations available

Input - Demand of user, solar radiations available

Output - Power supplied from solar panel, power taken from grid

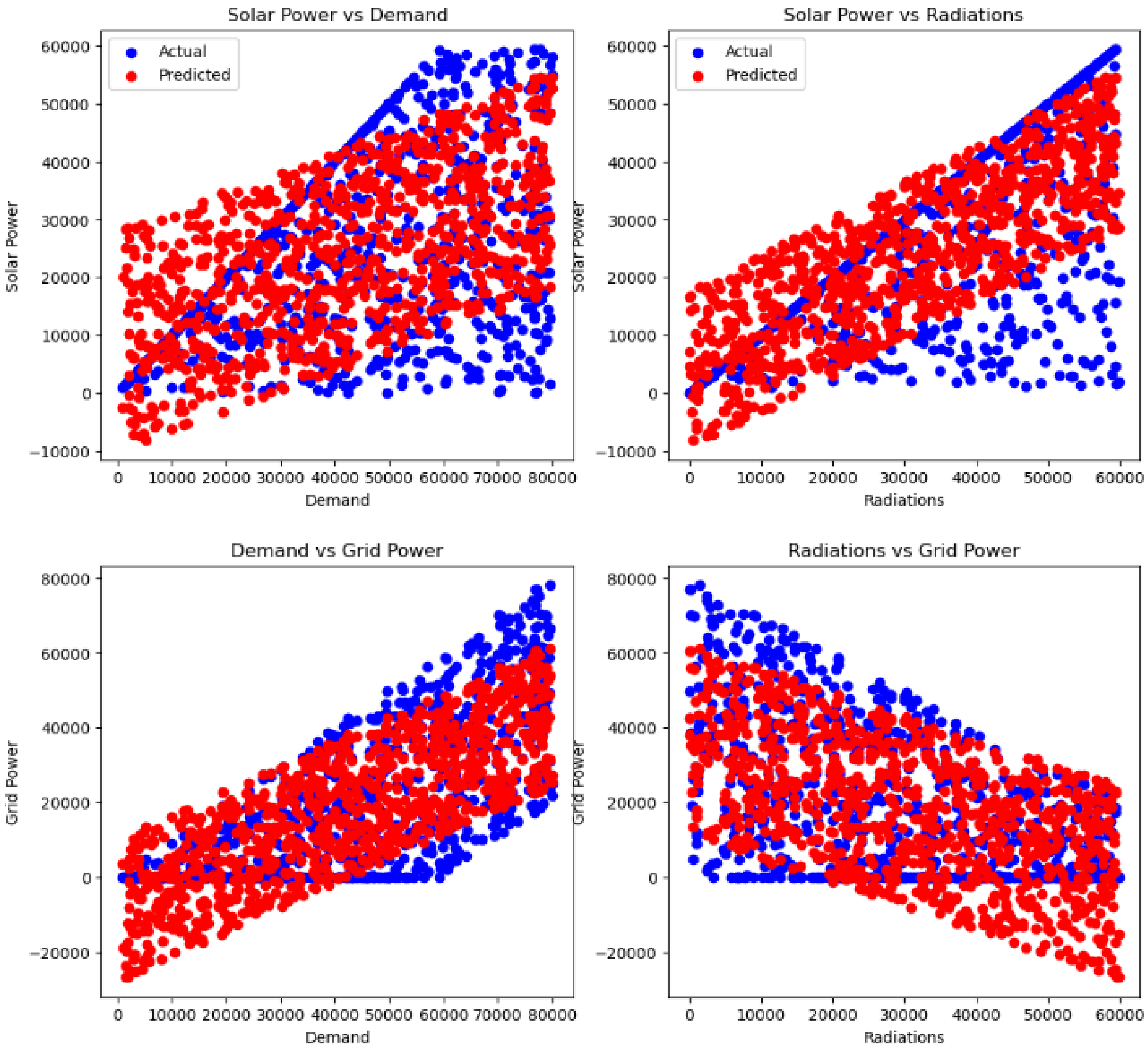
As some actual data wasn't present so we designed the dataset ourselves. The logic used was: If demand is less than the radiations available, then solar power would supply the entire demand and grid power would be zero. If demand is greater than the solar radiations available then solar power would serve its maximum limit and remaining would be supplied from grid.

Based on this, we designed the dataset. A sample dataset is as follows:

```
Demand,Radiations,Solar_Power,Grid_Power
50081,22929,22929,27152
14025,20643,14025,0
39095,7859,7859,31236
66331,9424,9424,56907
17970,11754,11754,6216
60114,28480,28480,31634
40565,25724,25724,14841
33918,51100,33918,0
17553,33272,17553,0
25432,47961,25432,0
61955,2027,2027,59928
7607,20881,7607,0
41039,43382,41039,0
42075,32638,32638,9437
```

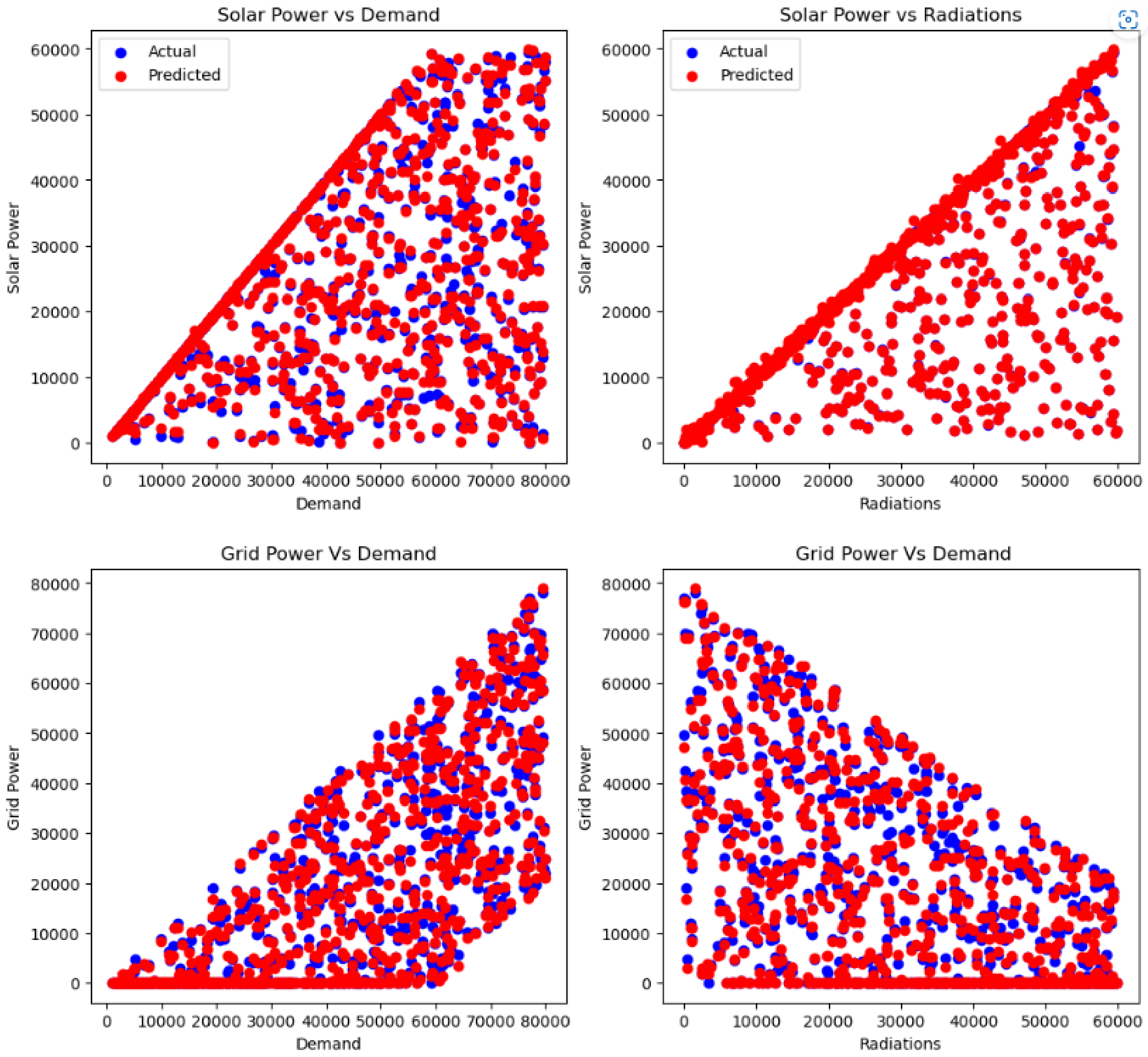
i) Model 1 - Linear regression

```
RMSE: 7716.516184156786
Mean squared error: 59544622.02
R-squared: 0.81
```



ii) Model 2 - Decision Tree

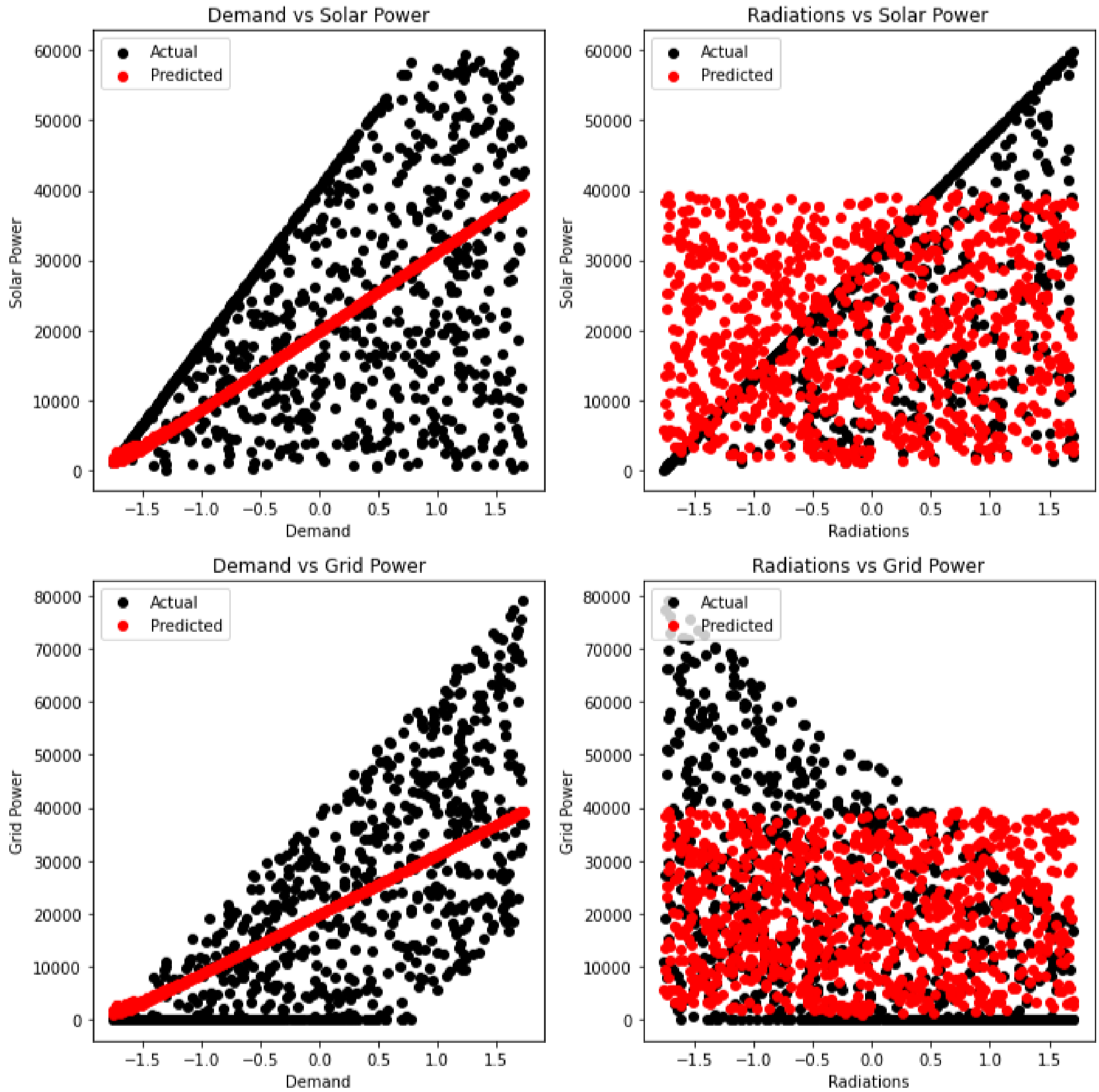
```
RMSE: 761.8834220286656
R-squared score: 1.00
```



iii) Model 3 - Neural Networks

Mean Squared Error: 198279008.00

Mean Absolute Error: 11405.31



On looking at the RMSE error values, we can say that decision tree is the best as it overlaps completely with the actual values. In terms of time complexity, SVM takes a very duration to train the model whereas decision tree and linear regression are very fast.

Integrating the model to obtain the final price:

After training all the models, now we integrated them to fulfill the final purpose of our project. We will take weather conditions and demand of user as input and give the final cost as output. The flowchart of this section of project will be as follows:

i. We gave weather conditions as input to dataset 1 and got the solar radiations as output.
ii. After this, we take demand of user and radiations received in step I as input to the dataset 4 to get the solar power and grid power.
iii. Using dataset 2 and dataset 3, we will find the price of the power from each source.
iv. We will add both the prices received to find the total cost user has to pay.
v. Also, using the logic for creating datasets, we mathematically calculated the actual values that will come for the desired demand and at the radiations found using dataset 1. Then, we compared it with the price obtained in Step IV and found the error obtained in our answers.

During running the models, we do face some odd values such as negative prices which we have to deal separately by mentioning suitable conditions such as for negative price, we set price = 0.

Now, while integrating we took two cases:

A. We used linear regression model for all our datasets and found the result using that.
B. We used the best case model for each dataset based on the lowest RMSE error values. Like, for dataset1, neural networks were giving least error so we trained first dataset using that and similarly second dataset using decision tree because of least error value.

From these both cases, we observed that the one with all linear regression trained datasets, we had a large error from our desired value. While, when we took the most efficient model to train each dataset according to their requirements, our experiment run values were comparatively closer to the mathematically calculated values and the error was less.

We receive output in the following format:

```
Demand from user:  5000
Power taken from solar panel:  [-8503.0044361]
Power taken from power grid:  [13503.0044361]
Cost of solar power used:  27.406045016669168
Cost of grid power used:  89514.14867243047
Final Total Price (Predicted):  89541.55471744714
Final Total Price (Calculated):  321709.77
Error:  72.16697686319966
```

In this way, we successfully trained a model to dynamically check for solar power and decide how much we can use solar power to charge our vehicles and how much we need to borrow from power grid.

Chapter-6

Comparison

1. **Use of solar energy as primary power source:** Our model utilises solar energy as the primary power source for charging electric vehicles. Our design, by utilising solar energy, has various benefits, including a lower carbon footprint and potentially lower energy expenses for the user. This makes the model unique and different from traditional ones relying on grid electricity as the primary power source.

2. **Integration of multiple datasets:** Our charging calculator integrates multiple datasets to deliver a more thorough and precise cost estimate. For instance, we have incorporated the following dataset- solar irradiance, solar cost, grid cost, and demand of the users to develop a comprehensive calculator. By this, we can provide more reliable and accurate cost estimate to our users.

3. **Use of machine learning algorithms:** Our model utlises machine learning algorithms to predict cost of the solar radiation, grid power and overall power demand flow. The algorithms used are linear regression, neural networks, decision tree, and support vector machine. The benefit of these algorithms is that they can learn from data and gradually improve their predictions. These integrated algorithm technique helps to predict cost more accurately.

4. **Customization for location and vehicle type:** Users can input their location and vehicle type in the charging calculator. This provides more customized and accurate predictions of charging costs. This customization is very crucial as location and vehicle type can significantly impact charging costs. In contrast to models that rely on broad assumptions about location and vehicle type, we can offer the users with more accurate and reliable cost predictions by taking the real time input.

Chapter-7

Conclusion and Future Work

7.1 Future Work:

7.1.1 **Expansion of the dataset:** One of the potential areas of future work is to expand the dataset by adding more variables such as battery type, charging time, and energy consumption. This can improve the accuracy of our model and make it more suitable for a wider range of EV users.

7.1.2 **Real-time updates:** Our model could be further improved by incorporating real-time updates of solar irradiance and grid power prices. This will make the calculator more precise and up-to-date, providing users with the most accurate predictions of charging costs.

7.1.3 **Integration of renewable energy sources:** Another potential area of future work is to incorporate other renewable energy sources, such as wind and hydropower, to provide users with a more sustainable charging option. This could also improve the accuracy and reliability of our model.

7.1.4 **Mobile application:** Developing a mobile application for our model can make it more user-friendly and accessible to a wider range of users. This can allow users to access the calculator on-the-go, making it more convenient to use and increasing its overall utility.

7.1.5 **User feedback:** Gathering feedback from users can help identify areas for improvement and guide future development of the calculator. This can be done through surveys, feedback forms, and user testing, allowing us to continuously improve and refine our model.

7.1.6 **Battery technology:** As battery technology continues to improve, it is expected to have a significant impact on the cost of electric vehicles. The prediction model can be used to analyze the impact of advancements in battery technology on electric vehicle pricing.

7.1.7 **Incorporate sustainability metrics:** We can include sustainability metrics, such as carbon emissions and energy efficiency, into our model to provide users with a more comprehensive understanding of the environmental impact of their charging choices.

7.2 Conclusion:

Our study has developed a charging calculator and explored EV charging stations, and in combination, we've presented an unparalleled solution that caters to the ever-increasing demand for affordable and sustainable energy alternatives among users of electric vehicles. Our model has secured its spot among other existing models, being dependent on solar energy as the chief source of power, having multiple datasets integration, and providing precise and personalized estimates of charging costs with the help of machine learning algorithms.

As the globe continues to move towards renewable energy and sustainable lifestyles, the demand for dependable and effective charging solutions for electric vehicles will only grow. Our concept, which offers the possibility of personalization and accuracy, moves us one step closer to meeting this demand and ensuring that sustainable mobility is available to everybody.

In order to become the ultimate resource for electric vehicle users seeking eco-friendly and budget-friendly solutions, there are a few areas we must focus on. Expanding our dataset by including additional locations and weather conditions is a top priority.

We have demonstrated the effectiveness of merging renewable energy sources, data analytics, and machine learning algorithms as cutting-edge solutions for a greener future in order to stimulate greater research and development in the field of sustainable practises and clean energy. By doing this, we seek to inspire people and organisations to adopt these sustainable practises and their potential to usher in a better future.

References

1 The U.S. Department of Energy's Alternative Fuels Data Center (AFDC) (https://afdc.energy.gov/)

2 The International Energy Agency (IEA) (https://www.iea.org/)

3 The National Renewable Energy Laboratory (NREL) (https://www.nrel.gov/)

4 The Electric Power Research Institute (EPRI) (https://www.epri.com/)

5 The Smart Electric Power Alliance (SEPA) (https://sepapower.org/)

6 Azam, Farooque & Priyadarshi, Neeraj & Nagar, Harish & Kumar, Sunil & Bhoi, Akash Kumar. (2021). *An Overview of Solar-Powered Electric Vehicle Charging in Vehicular Adhoc Network.* [online]

6.1 Available:https://www.researchgate.net/publication/347168443_An_Overview_of_Solar-Powered_Electric_Vehicle_Charging_in_Vehicular_Adhoc_Network

7 B. Ye, J. Jiang, L. Miao, P. Yang, J. Li, and B. Shen, "Feasibility Study of a Solar-Powered Electric Vehicle Charging Station Model," *Energies,* vol. 8, no. 11, pp. 13265–13283, Nov. 2015.

8 Singh A, Shaha SS, G NP, Sekhar YR, Saboor S, Ghosh A. "Design and Analysis of a Solar-Powered Electric Vehicle Charging Station for Indian Cities." *World Electric Vehicle Journal.* 2021.

9 Q. Dai, J. Liu, and Q. Wei, "Optimal Photovoltaic/Battery Energy Storage/Electric Vehicle Charging Station Design Based on Multi-Agent Particle Swarm Optimization Algorithm," *Sustainability*, vol. 11, no. 7, p. 1973, Apr. 2019.

10 Home Charging calculator (https://e-amrit.niti.gov.in/home-charging-calculator)