Cost Estimation for Electric Vehicle Charging Stations

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***Abstract*—Considering the current environmental conditions, the demand for electric vehicles and charging stations are rising in the field of transportation. Cost estimation of charging stations becomes a matter of concern in determining the feasibility of building such facilities. In this paper, we propose a method to estimate the cost of electric vehicle charging using ExtraTreesRegressor as the machine learning model. We explored the dependency of the power of solar panels on the irradiance and temperature of the area. Finally, we analyzed the variation in cost for EV charging as this power changes.**

***Index Terms*—Electric vehicle, charging station, cost estimation, cost factors, cost models, case studies, challenges, and research directions.**

I. Introduction

Electric Vehicles are a promising technology in the coming times due to their pollution-free nature. However, installing and operating EV charging stations entail significant costs, and accurate cost estimation is crucial for stakeholders involved in the charging infrastructure's planning, development, and operation. The charging cost is calculated at the time of charging. There is yet to be a method to determine the cost of setting up an electric vehicle beforehand. The aim of this research paper focuses on a method to estimate the charging cost by establishing a relation between weather conditions and irradiance using Machine Learning. The paper also discusses various cost factors, cost models, tools, and case studies related to EV charging stations. Finally, the paper identifies future research directions to improve the accuracy of cost estimation for EV charging infrastructure.

II. Data Foundation

To calculate the cost, we first need the solar panel output power. For that, we need the irradiance and temperature of the environment. Temperature can be extracted from weather APIs. However, There is currently no API that gives the current irradiance data. Thus, the irradiance was estimated using the weather data. For that, a Machine Learning model was used, and the data was taken from openweathermap.com and some private institutes. Below mentioned are the various sources of the data.

1) Weather Data were taken from openweathermap API - Hourly Data for 5 years.
2) Irradiance Data were taken from Indian Institute of Technology Ropar.
3) Solar Panels were simulated in MATLAB, and Power output data were taken from that.

III. Proposed Method

By looking at the complexity of the overall problem, we have divided the whole project into three major parts:

1) Estimating the irradiance from the current weather data.
2) Finding the maximum power point for the solar cell using irradiance and voltage.
3) Estimating the final cost of charging.

The first two will be solved using Machine Learning Models, while the third one will be solved using mathematical models.

A. Logical Data Model

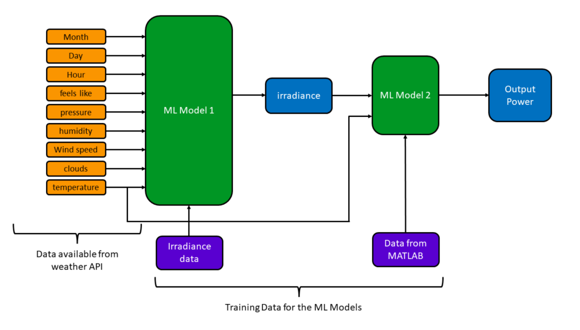

Fig. 1. Figure depicting the model flow.

There are two Machine Learning Models in our approach. Both are ExtraTreesRegressor. The first model predicts the irradiance from the current weather data. The second model uses the irradiance value along with the temperature and predicts the power output of the solar channel.

After this, our system has a cost model which uses that power output and calculates the cost of charging. The cost model considers many factors for the calculation, as shown in the section on mathematical interpretation.

IV. Observations

Various observations were made while solving the problem. Some of them are shown below:

A. Correlation

The correlation between weather data and irradiance is shown in Fig. 2. This shows us the interdependence of various factors.
The correlation of temperature and irradiance with power output is shown in Fig. 3. This shows us that power is directly related to irradiance and inversely related to temperature. These relations indicate that an ML model can be used to learn the patterns between all these parameters.

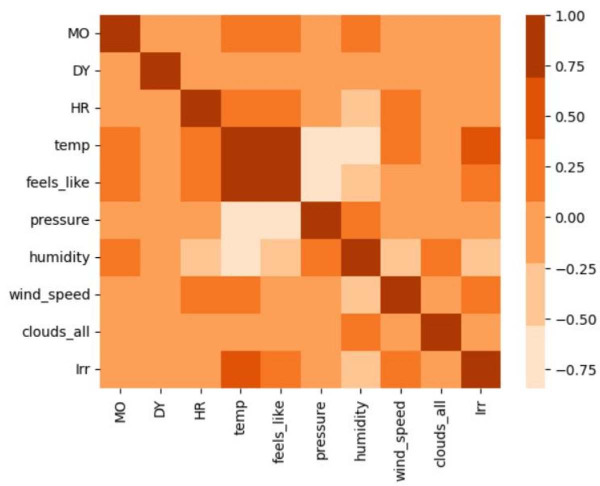

Fig. 2. Correlation between weather data and irradiance.

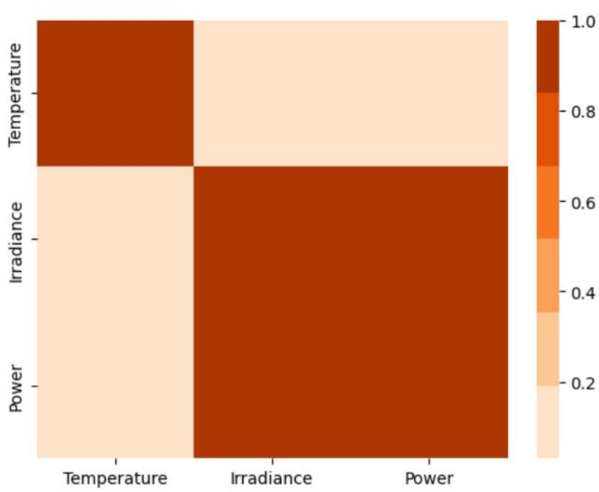

Fig. 3. Correlation between temperature-irradiance and power.

B. Predictions

The accuracies and r2 score are as follows:
For Weather-Irradiance model:

```
From Training Data:
r2 = 0.9944669453533349
From Testing Data:
explained variance = 0.9954033907828326
mse = 478.03450253653455
r2 = 0.9954008615380368
```

For Temperature-Irradiance-Power model:

```
From Training Data:
r2 = 0.9624589485306134
From Testing Data:
explained variance = 0.9996553155918964
mse = 3.946169333477804
r2 = 0.9995885568217695
```

Plots in Fig. 4 and Fig. 5 show the actual output and the predicted output for both models (Irradiance and Power).
By looking at them, we can conclude that our model is highly efficient as both plots almost overlap.

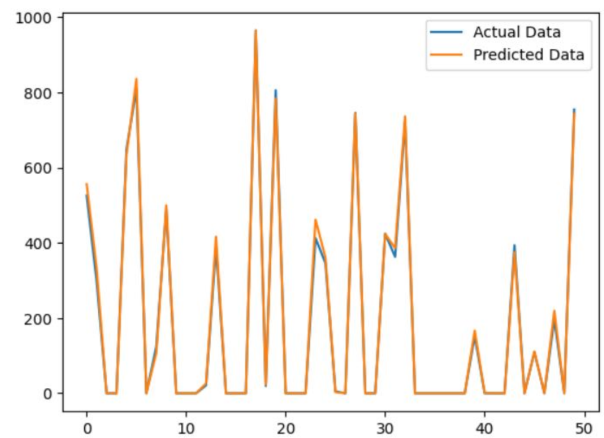

Fig. 4. Weather-Irradiance model predictions.

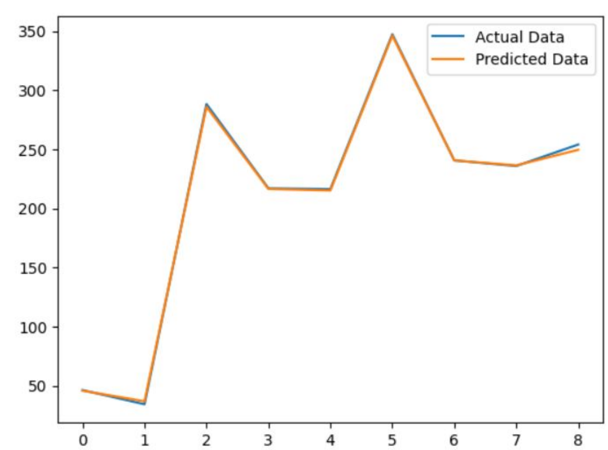

Fig. 5. Temperature-Irradiance-Power model predictions.

V. Mathematical Interpretation

Various factors have been considered for the cost calculation.

A. Solar Charging Time vs Grid Charging Time

Choosing the duration for solar energy is crucial. For observing the variation, we plotted various values of cost obtained for different t_solar. This graph depends on the time it is calculated. In the morning, we expect a good irradiance for long hours; hence charging using solar energy for long hours is better. However, in the evening, we should only use solar energy for a short duration.
This gives rise to a very important observation, i.e. the power output rate to the cost rate of the panel. The more this ratio, the more the duration we should use it. The moment the power-to-cost ratio of the grid becomes higher (generally, at the night power output of solar is less), we should use the grid.
The plots for various values of t_solar are shown in Fig. 6 (blue curve), which provides the cost estimation for various battery percentages (the time for which solar panel is used is varied). The x-axis has time in hours, and the y-axis has cost. Date and time: 16:00 11/05/2023. Location: Rupnagar, Punjab, India.

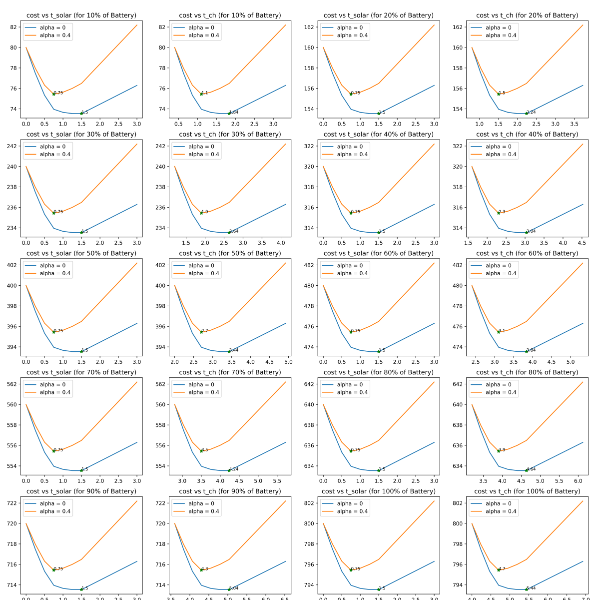

Fig. 6. Variation of t_solar for various battery percentages.

The plots for various values of t_solar considering alpha are shown in Fig. 6 (orange curve), which provides the cost estimation for various battery percentages (the time for which solar panel is used is varied). The x-axis has time in hours, and the y-axis has cost. Date and time: 16:00 11/05/2023. Location: Rupnagar, Punjab, India.

For the optimal cost, we have selected the minimum cost point and then used that t_solar to calculate the solar panel's power output. After that, the remaining energy is charged by the grid.

B. Rush Factor

Whenever there is a rush at the charging station, we should charge more for solar energy, as solar charging is slow. To account for this, we have considered a factor α. α varies between 0 and 1 depending on the rush. The solar charging cost is hence increased, and the overall cost and time are recalculated.

$$rate\_solar_{new} = rate\_solar_{old} \times (e^{\alpha})$$

The plot of The plot of cost vs alpha is shown in Fig. 7. The plot of charging time vs alpha is shown in Fig. 8.

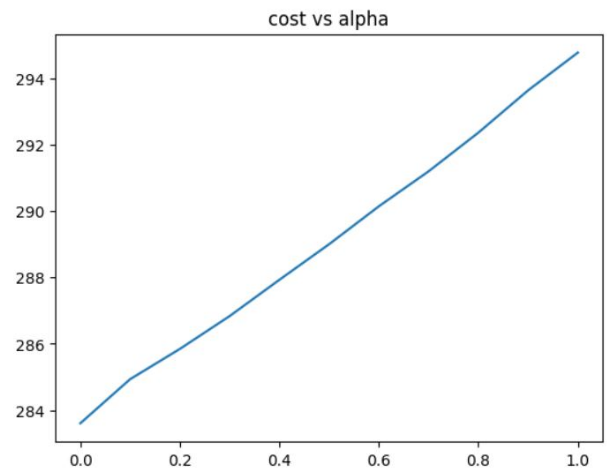

Fig. 7. Relation of cost wrt alpha.

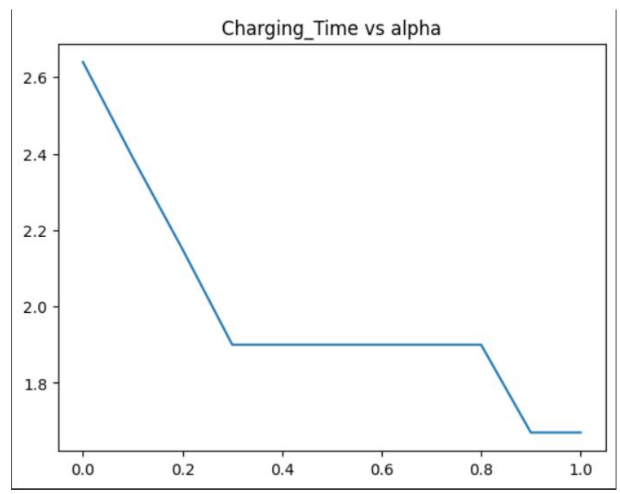

Fig. 8. Relation of cost wrt alpha.

C. Fixed Cost Factor

A charging station must have some fixed cost (like installation, etc.). This cost must be divided into all the customers and they should be charged appropriately. Our mathematical model has the below formula:

$$cost_{new} = cost_{old} + \frac{fixed\ \ cost}{number\ \ of\ \ transactions}$$

Number of transactions is the number of customers among which the fixed cost is to be distributed.

D. Prebooking Factor

The charging station maybe booked beforehand. If someone books a day before and comes on time, they should be charged less. Depending on the time at which the booking is done, there could be many categories. The math equation is given below:

$$cost_{new} = cost_{old} - \frac{prebooking\ \ category \times prebooking\ \ cost}{max\ \ prebooking\ \ category}$$

E. Priority Factor

If someone wants to charge first based on priority, they should be charged more. Similar to the previous factor, there may be categories:

$$cost_{new} = cost_{old} + \frac{priority\ \ rating \times priority\ \ cost}{max\ \ priority\ \ rating}$$

F. Profit Factor

The station owner may charge some extra money for profit. This factor is included as follows:

$$cost_{new} = cost_{old} \times (1 + profit\ \ margin)$$

VI. Results

The cost prediction was made considering all of the above factors. The results for 11/05/2023-16:00 at Rupnagar, Punjab, India are as follows:

```
latitude = 30.9688367
longitude = 76.526088
Successfully fetched the data from the API.
Month: 5.0
Day: 11.0
hour: 2.0
Temperature: 298.02
Feels_Like: 297.08
Pressure: 1005.0
Humidity: 20.0
Wind Speed: 2.31
Clouds: 0.0
alpha = 0.4
prebooking_category = 2
priority_rating = 2
base cost = 234.11
solar charging time = 1.25
total_charging_time = 2.4
cost after rush factor = 236.2
solar charging time = 1.0
total charging time = 2.15
cost after fixed cost factor = 256.2
cost after prebooking factor = 236.2
cost after priority factor = 268.2
cost after profit factor = 295.02
FINAL COST = 295.02
SOLAR CHARGING TIME = 1.0
TOTAL CHARGING TIME = 2.15
```

VII. Future Scope

Our current machine learning model for predicting the irradiance is trained on the data for a single region. Thus it may have errors in predicting the irradiance for some other regions.
This error can be diminished by training the model with two new features (longitude and latitude of the region).
Also, if we have the traffic data for a charging station, we can automate the alpha (rush factor) prediction according to the traffic.
We can also show the user different charging prices according to the time specified by the user in the application environment.

VIII. Conclusion

Two ML models were made to predict the irradiance and the power output. Both were ExtraTressRegressors and had over 99% accuracy, making our models reliable. Further, A cost calculation model was also made, considering the abovementioned 6 factors for the cost calculation. A webpage is also created for the same, which will support user interaction.
The overall code flow is shown in Fig. 9.

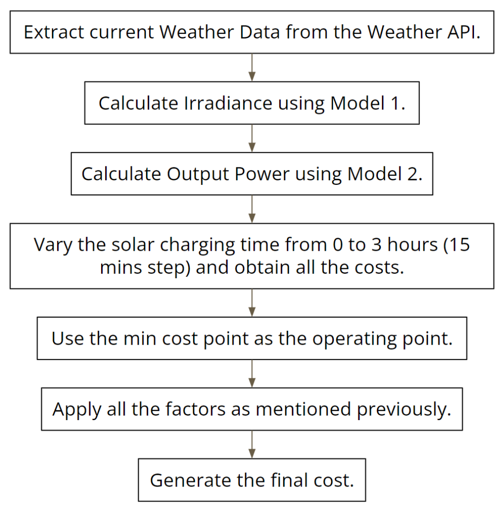

Fig. 9. Code Flow.

Acknowledgment

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