REDUCTION OF EV CHARGING COST THROUGH OPTIMAL SCHEDULING

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BONAFIDE CERTIFICATE

This is to certify that the project titled **REDUCTION OF EV CHARGING COST THROUGH OPTIMAL SCHEDULING** is a bonafide record of the work done by

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ABSTRACT

Electric vehicles (EVs) have been gaining popularity in recent years due to their reduced carbon emissions and lower operating costs compared to traditional gasoline vehicles. With the increasing adoption of EVs, there is a need to optimize the charging infrastructure to improve the charging experience for EV owners and reduce the cost of charging stations for operators. In this thesis, an optimal scheduling algorithm is proposed to tackle the problem of cost reduction for EV charging. Initially short-term load forecasting for the load demand on EV charging stations is carried out, which predicts the charging load of charging station for the next day. Furthermore, in addition to load forecasting, Monte Carlo simulations are executed to evaluate the power output of PV cells. The goal of this simulation is to evaluate the feasibility of using solar energy to power EV charging stations. The simulations will consider the amount of solar irradiance throughout the year at the location of charging station. By using this information, we can determine the potential energy output from solar panels and assess the viability of integrating solar energy into EV charging infrastructure.

Overall, the proposed research has the potential to provide significant benefits to users by reducing charging costs and improving the charging experience for EV owners. Additionally, the integration of solar energy can lead to further cost savings and contribute to the development of a more sustainable transportation system. By combining short-term load forecasting and Monte Carlo simulations, we can generate an optimal schedule for charging EVs that takes into account the available solar energy, helping to ensure that EV charging is cost-effective and sustainable.

Keywords: Electric Vehicle, Monte Carlo method, Short Term load forecasting

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LIST OF ABBREVIATIONS

EV	Electric Vehicle
PV	Photovoltaic
ACN	Adaptive Charging Network
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error
LGB	Light Gradient Boosting
JPL	Jet Propulsion Laboratory
PDF	Probability Density Function
CDF	Cumulative Distribution Function
LCOE	Levelized Cost of Energy

CHAPTER 1

INTRODUCTION

Electric grids are complex networks that use transmission lines to transport electricity from power stations to customers. They are a vital infrastructure component that underpins modern society, supplying power to practically all homes, businesses, industries, and other establishments. The popularity of electric vehicles, on the other hand, is growing because of their lower carbon emissions when compared to other types of vehicles. The EV ecosystem would not function without EV charging stations, which enable EV owners to go farther. Integrating EVs and EV charging stations into the electric grid may result in several issues, including an increase in the amount of electricity consumed by the grid, which could result in power outages or the need for costly grid upgrades. This challenge requires developing innovative solutions, such as load forecasting and optimal scheduling, to manage the load of EV charging stations and minimize the strain on the electric grid.

Creating smart charging technologies that can enable EV integration into the electric grid as a distributed energy resource represents another research challenge. This entails creating sophisticated algorithms and control systems that can sync EV charging with the requirements of the electrical grid. By allowing EVs to perform grid functions like demand response, energy storage, and voltage regulation, intelligent charging systems can assist in increasing the stability and dependability of the electric grid.

It is crucial to consider the interplay between these two systems to enable the successful integration of EVs and charging stations into the electrical grid. It is necessary to understand the EV charging demand's characteristics and how it changes over time and between different sites. It also requires developing innovative solutions to manage the load from charging stations, such as demand response programs that incentivize EV owners to charge their vehicles during off-peak periods.

Finally, analysis is required to understand how EV charging stations [3] are deployed and used. To suit the needs of various types of EVs and their owners, charging infrastructure must be designed and operated considering the location and positioning of charging stations. Additionally, it entails looking into business plans and legal frameworks that can facilitate the installation and operation of charging stations and foster the expansion of the EV ecosystem.

1.1 MOTIVATION

The increasing popularity of Electric vehicles is creating impactful changes in the energy industry. As more people opt for EVs, the demand for charging infrastructure increases, thereby creating stress on the functional electric grid. Managing load from EV is a challenging issue. The demand for EV charging is changing continuously and depends on various factors, such as time of day, day of the week, and seasonality. Different types of EV charging stations have different charging requirements. Hence this can further complicate load scheduling. Traditional methods of handling the load, such as increasing the grid's capacity, are not advisable as they are insufficient. Developing a different technique to manage load from EV charging stations is essential while maintaining efficient and reliable energy systems.

Recent advances in Artificial Intelligence have provided new techniques to perform forecasting. These techniques can identify and analyze the hidden trends in datasets. By using these techniques, cost of charging in EV charging station can be optimized and ensure power is utilized efficiently.

Load forecasting and optimal scheduling of EV charging stations are critical research areas essential for the EV market's sustainable growth. Our research aims to explore the use of advanced data analytics techniques to address this challenge and develop innovative solutions that can help reduce the strain on the power grid. We believe that our approach has the potential to make a significant contribution to this vital research area and help support the transition to a low-carbon economy.

1.2 OBJECTIVE

The followings include the significant objectives of this project work:

- Collection of statistical data on load demand and solar energy for a particular EV charging station
- Exploring various short-term load forecasting techniques and algorithms for predicting the load demand for a charging station at a particular instance of time

- Exploring and evaluating the prediction of Solar irradiance for an alternate source of renewable energy
- Exploring load scheduling algorithms with the help of the available forecasted load and solar energy
- Implementation and optimization of the technique mentioned above for minimizing the operation cost.

1.3 ORGANISATION OF THESIS

The complete report is documented in 5 chapters:

- Chapter 1 gives a short introduction to the project's objectives and the motivation behind choosing this project.
- Chapter 2 discusses relevant literature and presents a survey of the forecasting techniques, and application of scheduling algorithms for solving optimization problems.
- Chapter 3 elaborates on the methodology of the project. It provides details about the Machine Learning algorithms that were used for the forecasting of load demand and evaluation of PV power. It also elaborates on the proposed scheduling algorithm and different power consumption cases.
- Chapter 4 describes the test result for the most appropriate Machine Learning algorithms used to forecast the load demand and solar energy. The associated charging cost of the charging station after the implementation of optimization algorithms and a comparison between the performance of those algorithms are also discussed.
- Chapter 5 concludes the thesis with the performance of the used algorithms and future scope.

CHAPTER 2

LITERATURE REVIEW

This chapter briefly reviews the concept of electric vehicle charging and algorithms for optimizing the cost of charging. Previous methods used by other researchers are explored and touched upon.

2.1 EV'S AND THEIR CHARGING NATURE

Electric Vehicles (EVs) are different from the carbon-fueled vehicles of today. Their charging nature varies significantly and is more similar to charging an electric device like a mobile than refueling a car. Their sudden rise in popularity will create unprecedented demand for the electric grid. Improper and uncontrolled recharging at stations will lead to inefficient utilization of the charging station's resources. Users drop off vehicles at set times, and the tariff rates vary throughout the day. Relying solely on the grid for supply is also costly for the owner of the charging station. All this must be accounted for when charging the vehicle. The need for a structured scheduling algorithm is felt when looking at these constraints.

2.2 CONCEPT OF OPTIMAL CHARGE SCHEDULING

Looking at these constraints, the scheduling algorithm should primarily aim to minimize the cost of charging. Specific units are drawn from the grid and PV source whenever. It now becomes the task of determining when these planned units must be drawn from the grid to reduce the average cost of each unit consumed.

2.2.1 Zachary J. Lee et al. (2019) [5] has employed the idea of using variable charging rates for each charging port. Individual users are allotted a 'Laxity' based on their arrival and departure times and power demand. A laxity of zero means that EV is charged at the highest rate over the total duration of its charging to satisfy its energy requirement. A higher value of laxity implies that there is more flexibility in satisfying its energy requirement. The paper has employed GMM (Gaussian Mixture Model) [1] to predict and model the user behavior, primarily their arrival and departure natures. In statistics, a mixture model is a probabilistic model that represents the presence of subpopulations in the entire population without requiring that an observed dataset should identify the sub-population to which an individual observation belongs.

2.2.2 Mohammed Sulthan S et al. (2022) [8] proposed an algorithm for scheduling electric vehicle charging based on predicted solar PV generation and vehicle information is promising but has limitations. It assumes accurate solar power generation predictions and uninterruptible charging and does not consider charging station availability or the number of EVs present. However, it is a step towards efficient and sustainable charging strategies for EVs, and future research can improve upon it by considering additional factors.

According to the studies by Qian et al. [6] and Bai et al. [9], EV charging can be optimized through dynamic prediction of charging demand and scheduling optimization.

2.3 SOLAR POWER AND ALTERNATIVE SUPPLY

Solar power supply (PV) is also instrumental in determining the algorithm's workings. During the peak hours of the day, when the grid cost is high, utilizing the power from the PV source is economical. Deciding whether to draw from the grid or PV depends on the algorithm, based on various factors. While a lot of studies have addressed the issue of scheduling of EV charging to utilize on-site solar generation, it is generally assumed that solar capacity is fixed.

Zachary J. Lee et al. (2019) [5] use the ACN-Data dataset and the learned distributions to solve the particular problem of how past data can be used to optimally size on-site solar generation to reduce the cost of charging EV in workplace.

2.4 SUMMARY

Overall, optimal charge scheduling for EVs is crucial for efficient and cost-effective charging, especially as the demand for EVs continues to rise. Different algorithms have been proposed, such as using variable charging rates based on user laxity and predicting solar PV generation. However, there are still limitations and room for improvement in considering additional factors such as charging station availability and optimizing solar generation capacity. As EVs become more prevalent, it will be increasingly important to develop practical scheduling algorithms to ensure the efficient use of charging resources and minimize costs for both charging station owners and EV owners.

CHAPTER 3

METHODOLOGY

3.1 FORECASTING OF ENERGY DEMAND

The Adaptive Charging Network (ACN) dataset of the JPL location is used to forecast energy demand and synthesize new data for scheduling. It is a publicly available dataset that includes data on private workplace charging stations. The data was highly clustered and random and thus required significant preprocessing. The preprocessing steps can be summarized into three main stages: data cleaning, transformation, and preparation.

In the first stage, data cleaning removes irrelevant data, checks for completeness and correctness, and addresses any missing values. This also includes checking for expected data types, and the values in each column were within the expected range. In the second stage, the data was initially provided in GMT format, which was inappropriate for the analysis. Therefore, the data was converted to the local time of the station.

In the third stage, the total duration of stay for each EV was computed. With the total duration of stay for each EV, power demand was equally distributed across their period of stay in the station. This process was repeated over all the EVs; the per-hour load demand was obtained through this. Moreover, this was done for all the days in the dataset. The per-hour load demand was used as input for forecasting energy demand. Multiple algorithms were used in the next day's energy forecast. The critical Machine Learning models' well-performing algorithms are listed in upcoming sections.

3.1.1 Random Forest Regressor

It is a supervised learning technique that can be used for both regressions and classification problems. It belongs to the concept of ensemble learning. In this model, combining multiple decision tree classifiers is used to solve a complex problem and improve the model's performance. As the model's name describes, that random forest classifier uses multiple decision trees, which has been discussed in [4], with input as various subsets of given input and takes the average value as the final output value. As the number of decision trees increases, the model accuracy increases. Since multiple decision trees are used for slightly varying data subsets for each tree respectively, the overfitting of each tree is averaged out to get output. Hence the overfitting problem is eliminated. The model runs multiple decision trees in parallel. It also maintains accuracy even if parts of the data are missing.

Before using the model, the dataset should consist of some true values in the feature variable of the dataset so that the classifier would be able to predict accurate results rather than a guessed result. The predictions from each tree must have very low correlations. As in this project, the dataset consists of only two features, namely date and power delivered, so there is no problem with correlations, and since the model is used to predict only the next day's power consumption, most of the actual output values are used; hence the problem of guessing of output also eliminated.

The random forest regression algorithm proceeds in the following order:

Step 1) Bootstrap sampling: Randomly select a subset of data from the original dataset using bootstrap sampling.

Step 2) Build decision trees: For each subset of data created in the previous step, build a decision tree to predict the value of the target variable. The decision tree can use different splitting criteria, such as information gain, Gini impurity, or entropy.

Step 3) Repeat steps 1-2 for a specified number of trees to create a forest of decision trees.

Step 4) Predict: To predict a new input, use all the trees in the forest and combine their predictions using an average. This produces a more robust and accurate prediction than a single decision tree.

Step 5) Evaluate the model: Evaluate the performance of the random forest model using the testing set. In this thesis, the evaluation metrics used are Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

Step 6) Tune the hyperparameters: Tune the hyperparameters of the random forest model to improve its performance. Hyperparameters can include,

- the number of trees in the forest,
- the maximum depth of the trees,
- the minimum number of samples required to split a node, and
- the maximum number of features considered for each split.

Step 7) Deploy the model: Deploy the random forest model to make predictions on new unseen data.

3.1.2 Prophet Model

It is a regressive supervised learning type used for time series regressive problems. Unlike other models, it has a seasonal period of months or years, which cannot be used for complex seasonal trends. The model is easy to use and does not require prior knowledge of statistical concepts, and the prophet model also handles outliers and missing data better than other models.

It is a regressive additive model that decomposes a time series into trend, seasonality, and holiday components and models them separately, as mentioned in Equation 3.1. It uses a Bayesian approach to estimate the model's parameters and incorporate uncertainty in the predictions.

$$Y_t = G_t + S_t + H_t + X_t + Z_t \tag{3.1}$$

Here,

G_t = trend,

S_t = Seasonality,

H_t = Holiday Effects,

X_t = Other Regressors,

Z_t = Noise.

(a) Seasonality

Seasonality refers to repetitive patterns in a time series that occur at fixed intervals, such as daily, weekly, monthly, or yearly. Seasonality can be caused by various factors, such as weather, holidays, events, or social behaviour, and can significantly affect the behavior of the time series. Prophet uses a Fourier series to model the seasonality component of the time series, where each seasonal pattern is represented as a sum of harmonics with different frequencies and amplitudes.

The seasonality in Prophet is mentioned in Equation 3.2.

$$S_t = \sum_{n=1}^{N} \left(a_n \cos\frac{2\pi nt}{P} + b_n \sin\frac{2\pi nt}{P} \right) \tag{3.2}$$

Here, P = period of seasonality

(b) Holidays

Holidays refer to special events or occasions that can affect the behaviour of a time series. Including holidays in the model can improve the accuracy of the forecasts and help capture the effects of the events on the time series. It has the comfy flexibility of adding holidays and neighbouring days to the modelling.

(c) Trend

Trend refers to the long-term behaviour of a time series, which captures the overall pattern and direction of the data. The trend can be linear, nonlinear, or a combination of both, depending on the nature of the data. The trend changepoints are the points in time where the trend changes direction or curvature. It automatically detects the changepoints using a Bayesian changepoint detection algorithm, which balances the model's goodness of fit with the trend's complexity.

It also allows for including nonlinear components in the trend, such as logistic growth or saturating growth, which can be necessary for modelling data with nonlinear trends. Nonlinear components can be specified by adding additional columns to the input data frame with appropriate transformations of the variables.

The sigmoid type saturating trend is mentioned in Equation 3.3.

$$G_t = \frac{C_t}{(1+e^{-k(t-m)})} \tag{3.3}$$

Here, C_t = maximum capacity,

k = growth rate,

m = offset.

(d) Noise

Noise refers to the random fluctuations or errors in a time series that the trend and seasonality components cannot explain. Noise can arise due to various factors such as measurement errors, sampling variations, or unobserved factors and can significantly affect the accuracy of the forecasts. The noise component uses a normal distribution with zero mean and a scale parameter estimated from the data. The scale parameter, also known as the error term, represents the magnitude of the noise in the data and is estimated using maximum likelihood estimation. The standard distribution assumption allows for the calculation of prediction intervals, which measure uncertainty around the forecasts.

The noise function is mentioned in Equation 3.4.

$$N(0, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{x^2}{\sigma^2}} \tag{3.4}$$

Here,

σ = deviation of noise.

The Algorithm for Prophet is as follows:

Step 1) Trend modelling: This models the trend in the data using a piecewise linear function that can accommodate both linear and nonlinear trends. It uses a Bayesian changepoint detection algorithm to automatically identify the points where the trend changes direction or slope.

Step 2) Seasonality modeling: This models the seasonality in the data using the Fourier series. It can handle multiple periodicities, such as daily, weekly, monthly, and yearly patterns, and automatically selects the best periodicities based on the data.

Step 3) Holiday modeling: It allows the user to specify a list of holidays and their associated prior impact on the target variable. It models the impact of holidays as a piecewise linear function with a user-specified changepoint prior.

Step 4) Fitting the model: It fits the additive model using a Bayesian framework that estimates the parameters and uncertainties of the model using Markov Chain Monte Carlo (MCMC) sampling. The user can also specify additional parameters, such as seasonality strength, trend flexibility, and uncertainty interval width.

Step 5) Making predictions: Once the model is trained, the model can be used to make predictions for future time points. It generates a forecast for each time point and a prediction interval that captures the uncertainty in the forecast.

3.1.3 Light Gradient Boosting

Light Gradient Boosting (LGB) is a gradient-boosting framework using a tree-based learning algorithm to perform classification and regression tasks. Microsoft developed it and is known for its high efficiency and speed.

It uses a Gradient-based One-Side Sampling (GOSS) technique to reduce training time and memory usage. This combines gradient-based and random sampling to select a subset of the training data with high gradient values and low sample weights. It also allows it to focus on the most informative samples for the learning task and skip the less important ones, thus reducing the computation time and overfitting.

It also uses a feature called Histogram-based Gradient Boosting (HGB) to accelerate the training process. HGB creates histograms for the input features and uses them to calculate the gradient statistics instead of the traditional computation. This approach reduces the time and memory complexity of calculating the split point for each feature and increases the training speed. Additionally, several regularization techniques, such as L1 regularization, L2 regularization, and dropouts, are used to prevent overfitting and improve the model's generalization. It is like the decision tree algorithm, but the nodes and classification conditions increase as the iterations increase.

It follows the given algorithmic procedure:

Step 1) Initialization: Start with a single tree with a single leaf node that predicts the mean of the target variable.

Step 2) Iteration: In each iteration, a new decision tree is trained on the negative gradients of the previous trees, which are the differences between the true target values and the predictions of the previous trees. The new tree is trained on a subset of the data and a subset of the features, chosen randomly using a technique called feature bagging.

Step 3) Prediction: To make a prediction for a new instance, apply the prediction of each tree in the ensemble to the instance and sum the results.

Step 4) Regularization: It uses two regularization techniques: shrinkage and feature regularization. Shrinkage involves multiplying the prediction of each tree by a small number called the learning rate. Feature regularization involves randomly dropping some of the features during the training process, which helps to reduce overfitting.

3.2 SOLAR FORECASTING

Multiple factors have an impact on the power output of the PV module. Some of them are solar irradiance, the site's ambient temperature, and the module's characteristics. NASA's website [10] is used to obtain the value of solar irradiance of the Jet Propulsion Laboratory (JPL) location.

The steps followed to generate power output are given below,

Step 1) From the data obtained through NASA's website, all the data points were converted into hourly segments. This was done by dividing the entire data set into twenty-four segments, each representing one hour.

Step 2) It is necessary to identify the Probability Density Function (PDF), which all the multiple data points in each segment follow. So, to determine the suitable pdf for the obtained data, a goodness of fit test is performed. Through this, the shape parameters of the distribution for each segment would be identified.

Step 3) By utilizing the distribution parameters, randomly sampled solar irradiance is obtained through the inverse Cumulative Distribution Function (CDF) of the data set.

Step 4) Using the values of randomly sampled solar irradiance, the output power of the PV plant is obtained.

3.2.1 Mathematical Equations

1. Output power of PV plant [7]:

$$P_{PV}(t) = P_m \times \frac{G(t)}{G_o} \times \left(1 + \gamma \times (T_c - T_o)\right) \tag{3.5}$$

Here,

P_m is the maximum output power of the PV plant (76 kW),

G(t) = Solar irradiance (in W/m^2) received at t hour,

G_o = Reference solar irradiance = 1000 W/m^2,

γ = Temperature coefficient of the PV module = -0.41% /°C,

T_c = Cell temperature (in °C),

T_o = Reference temperature = 25°C.

2. The value of cell temperature:

$$T_c(t) = T_a + \frac{G(t)}{800} \times (T_{NOCT} - 20) \tag{3.6}$$

Here,

T_a = Ambient temperature = 25°C,

T_{NOCT} = Nominal operating cell temperature = 44°C.

3.3 SCHEDULING

The proposed algorithm collects information from the user when the vehicle arrives at the entrance of the charging station. The main input factors considered for the algorithm are:

- Vehicle arrival time
- Vehicle departure time
- Energy required.
- Availability of PV power for each hour
- Electricity tariff
- PV tariff

Time-of-Use (ToU) rate scheme from Southern California Edison (SCE) is adopted as a grid tariff. The value of the grid tariff is presented in Table 3.1 and is also depicted in Figure 3.1. Levelized Cost of Energy (LCOE) is considered for solar cost [5], which is $0.08 / kWh.

Duration	Rate
On-Peak	$0.25 / kWh
Mid-Peak	$0.09 / kWh
Off-Peak	$0.06 / kWh

Table 3.1 Grid Tariff

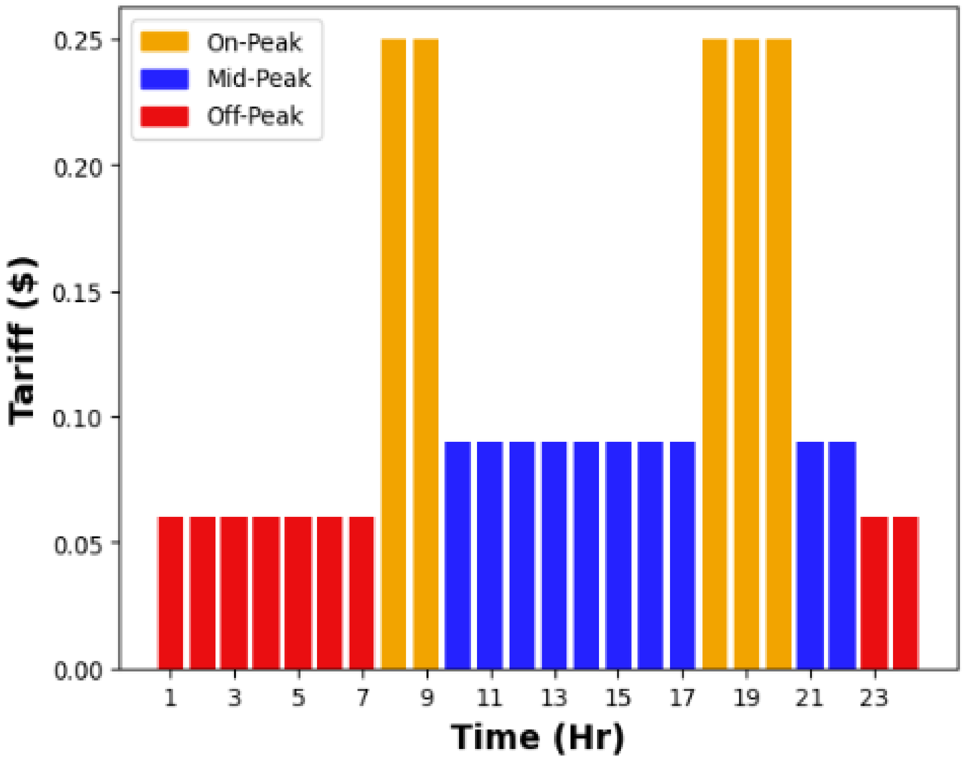

Figure 3.1 Grid tariff

Arrival, departure time, and Energy required are the values collected from the user. With the information collected, the algorithm decides the suitable charging rate and time slots to charge the vehicle. It is directed towards the suitable charging station to initiate the process. Each time slot is five minutes long. Initially, before identifying the time slots, the vehicle converts all the input data into five-minute data.

Details such as arrival and departure time are rounded off and then divided by five to get a single integer representing the time. However, the arrival time is rounded up to the next five minutes, and the departure time is rounded to the previous five minutes. The conversion of arrival and departure times for a single vehicle is presented in Table 3.2. Details such as Energy and tariffs are converted from per hour to per five minutes.

Type	Actual time (HH:MM:SS)	Rounded off time (HH:MM:SS)	Slot number
Arrival time	06:04:35	6:05:00	73
Departure time	11:37:35	11:35:00	139

Table 3.2 Data Conversion

PV power availability is obtained from Section 3.2. Using the details of PV power, the tariff rates of the grid, and LCOE, the algorithm effectively utilizes the power from PV cells during scheduling. Later, it calculates the charging cost for all slots between arrival and departure times. If there is availability of PV power and if the cost of PV charging is less than the tariff cost, then PV power is utilized to charge the electric vehicle. With the calculated values it identifies the slots during which the vehicle needs to be charged to minimize the cost. In addition, if excess solar power is available during a particular slot, the generated solar power is sent back to the grid.

3.3.1 Types of Analysis

Two different case studies are analysed. In the initial case study, only a single power rating (3kW) for charging is considered. In the second case study, slow and fast charging are considered for analysis and presented in Table 3.3. In case 2, there is a limit on the number of stations for each power rating which is also presented in Table 3.3.

Type of Chargers	Charging Power	Number of Stations
Slow Charging	3 kW	30
Fast Charging I	7 kW	20
Fast Charging II	11 kW	10

Table 3.3 Types of Chargers

For the first case, only slow charging was considered for all the available stations, and the number of stations was not considered. It is assumed that enough stations are available to accommodate the cars arriving for charging at any time. Hence, whenever a new car arrives, it is directed toward charging without considering the station's availability. Unlike the first case, there are charging stations with multiple charging rates of 3kW, 7kW, and 11kW with a limited number of stations, as mentioned in Table 3.3.

The charging rate varies for each vehicle. It is assigned based on the availability of the station and the energy required for the vehicle. Some vehicles have higher energy demand, which fast charging could only satisfy. Hence, for those vehicles, fast charging would be preferred. However, in rare scenarios, when the vehicle demands fast charging, fast charging stations would not be available. Therefore, in those extreme situations, slow charging is chosen to meet the demands. Even though the total energy demand could not be met, at least some of the demand would be met.

For both cases, the analysis is carried out as follows: (i) Uncontrolled charging, (ii) Controlled charging without a PV power source, and (iii) Controlled charging with a PV power source. Initially, Uncontrolled charging is considered. In this analysis, the vehicle initiates charging when it reaches the station, and charging time slots are not identified. The vehicle charges until the total energy demand is delivered. In rare scenarios, the total energy demand could not be met before the departure time. In those scenarios, it is charged continuously until the departure time.

The second analysis is Controlled charging without a PV power source. In this analysis, only the grid power is taken for charging the vehicle, and the algorithm provides the time slots during which the vehicle's charging cost would be minimized. The third analysis is Controlled charging with a PV power source. In the final analysis, the grid power and the power generated from PV cells are used to charge electric vehicles. The algorithm intelligently uses the PV power when the grid cost is higher than the LCOE and if enough PV power is available.

3.3.2 Synthesizing data

For scheduling, three important data are required from the user: arrival, departure time, and energy demanded. Hence, for scheduling, the required data are synthesized using the probability distribution function. The steps followed to generate data are given below,

Step 1) Identify the total energy demand from the forecasting of power carried out in Section 3.1.

Step 2) Using the historical data of energy demand, fit multiple pdf and identify the best-fitted distribution for the demand of energy by vehicles.

Step 3) Generate data points from the best-fitted distribution and identify the number of vehicles arriving on the forecasted day by using,

$$Total\ energy > \sum_{vehicle=1}^{N} Energy_{vehicle} \tag{3.7}$$

Where $Energy_{vehicle}$ is the energy demand of a single vehicle, and N is the number of vehicles. This process is iterated until the condition is dissatisfied. The maximum value of N for which this condition is satisfied is assumed to be the number of vehicles.

Step 4) Using the historical data of arrival, departure time, and energy demand, fit multiple pdf and generate N data points by identifying the best-fitted distribution for each data.

3.3.3 Proposed Algorithm

The complete algorithm to identify the best charging slots while using both grid and solar power to minimize the charging cost is represented in Table 3.4.

Steps	Procedure
Step-1	Load the arrival time (t_a), departure time (t_d) and energy required of the EV.
Step-2	Load the PV tariff (C_{pv}), grid tariff (C_{grid}) and available PV power (P_{pv}).
Step-3	Convert all input data into five-minute slots.
Step-4	Update the count on available charging stations and identify the suitable charging rate (R_{ch}), charging time (t_{ch}).
Step-5	Find the charging cost (C_{ch}) for all slots between t_a and t_d using, $$P_{req}(t) = R_{ch} - P_{pv}(t)$$ $$C_{ch}(t) = R_{ch} \times Tariff$$ $$Tariff = \begin{cases} C_{grid}(t) \text{ if } P_{req}(t) > 0 \text{ or } C_{pv} > C_{grid}(t) \\ C_{pv} \quad \text{otherwise} \end{cases}$$
Step-6	Identify the slots during which the charging cost is minimum.
Step-7	Schedule the vehicle to charge at the identified slots.

Table 3.4 Step by Step procedure of proposed algorithm

3.4 FLOWCHART OF THE WORK

The entire work of the thesis is summarized in Figure 3.2.

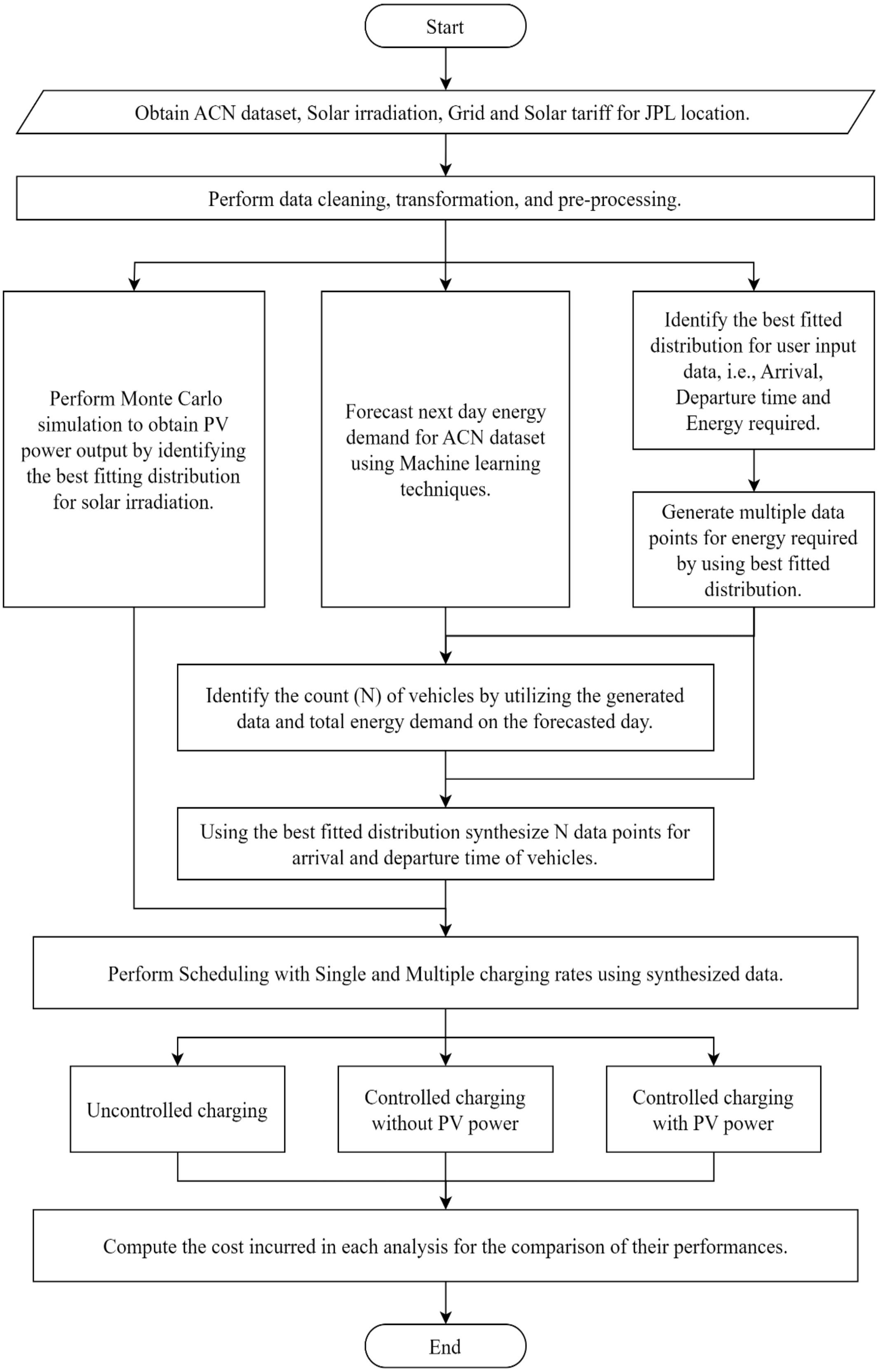

Figure 3.2 Flowchart of the complete work

CHAPTER 4

RESULTS AND DISCUSSION

4.1 ENERGY FORECASTING

The Adaptive Charging Network (ACN) dataset is used to predict the next day's energy consumption. The dataset was analyzed using multiple Machine Learning (ML) algorithms such as Prophet, Light gradient boosting, and Random Forest Regressor. In addition to Prophet, LGB, and Random Forest Regressor algorithms, models such as ARIMA [2], SARIMA, and SARIMAX models were also applied to predict the energy consumption for the next day.

4.1.1 Prophet Results

Prophet is an open-source time series forecasting model which uses Bayesian regression to model the trend and seasonality components. Figure 4.1 shows the next day's energy consumption data and the Prophet model's prediction.

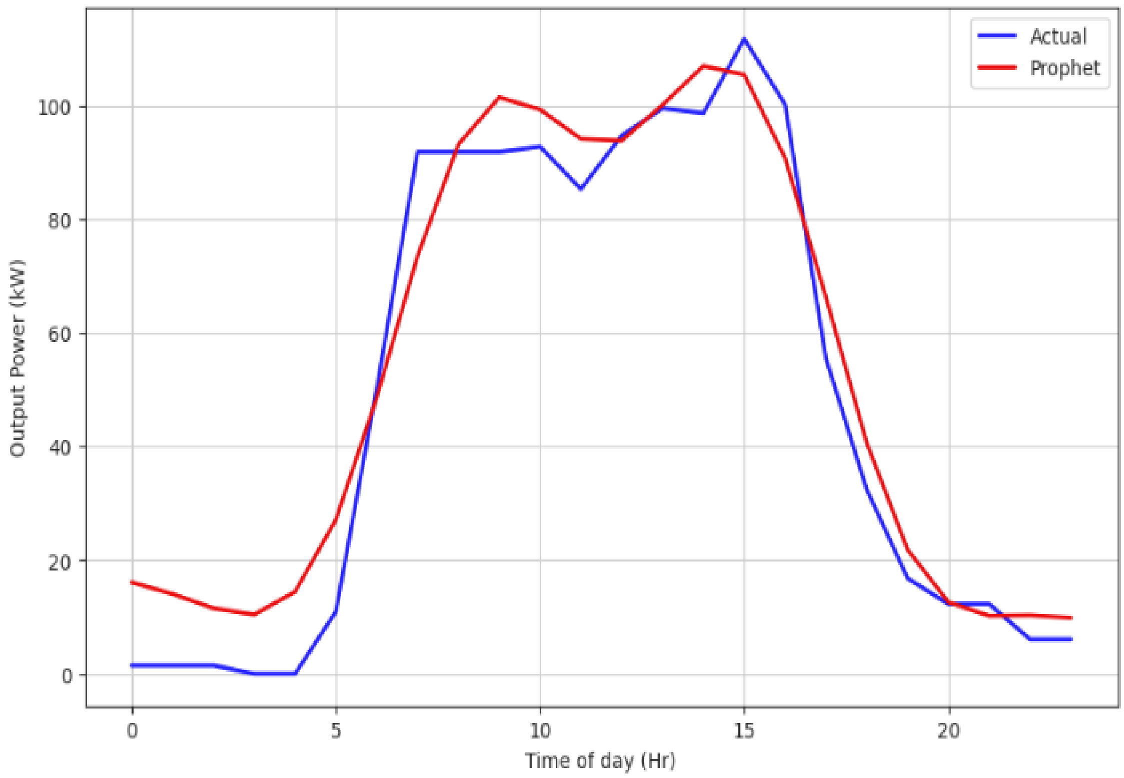

Figure 4.1 Prophet model's energy prediction

Figure 4.1 indicates that the Prophet model can capture the patterns and trends in data, resulting in a much more accurate energy consumption prediction. To evaluate the model's performance, two metrics were used, namely Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The performance metrics for the Prophet model are summarized in Table 4.1.

Metric	Value
MAE	7.68
RMSE	15.54

Table 4.1 Performance metrics for the Prophet

4.1.2 Light Gradient Boosting Results

Light Gradient Boosting (LGB) is a robust ensemble learning algorithm that uses a gradient-boosting framework to train multiple weak learners sequentially. Figure 4.2 shows the next day's energy consumption data and the Light Gradient Boosting model's prediction.

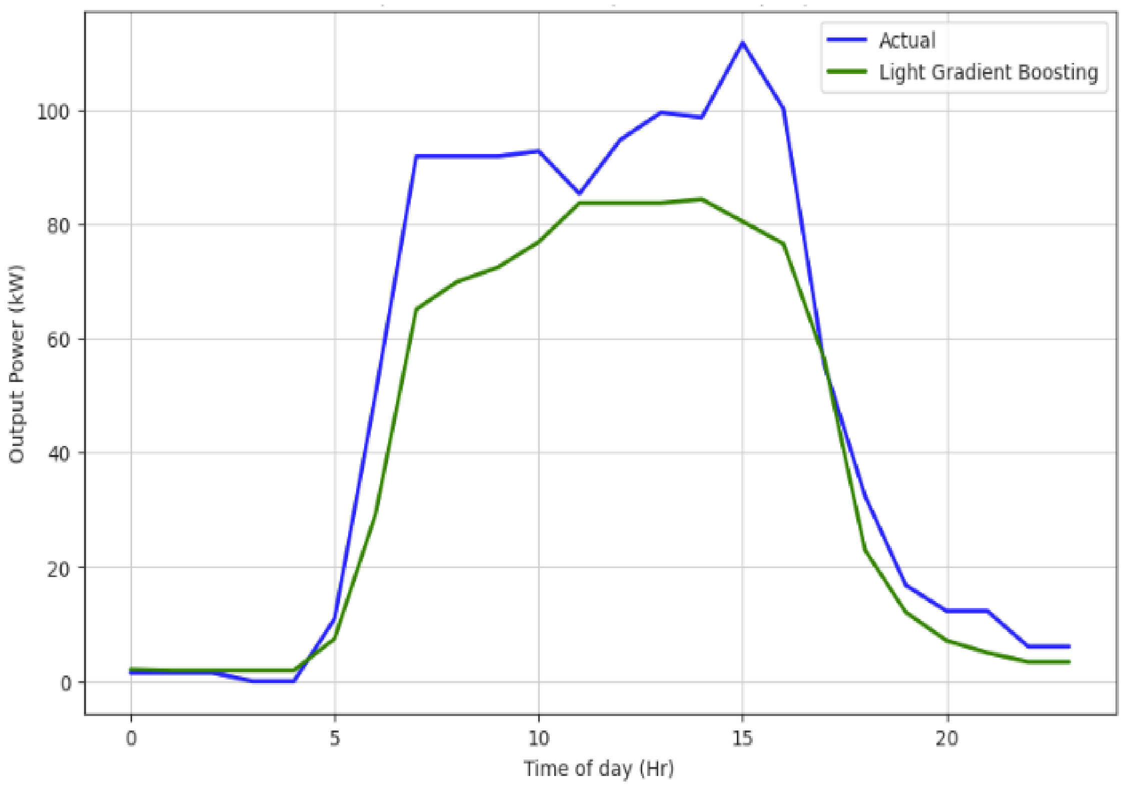

Figure 4.2 Light Gradient Boosting model's energy prediction

Although the model's prediction was accurate in the early and later part of the day, its accuracy decreased during the peak hours of the day. The difference between the actual and predicted values during the peak hours of the day was significant. The performance metrics for the Light Gradient Boosting model are summarized in Table 4.2.

Metric	Value
MAE	10.17
RMSE	13.85

Table 4.2 Performance metrics for the Light Gradient Boosting

4.1.3 Random Forest Regressor Results

Like LGB, Random Forest is a popular ensemble learning algorithm that uses a decision tree-based framework to improve generalization. Figure 4.3 shows the next day's energy consumption data and the prediction of the Light Gradient Boosting model.

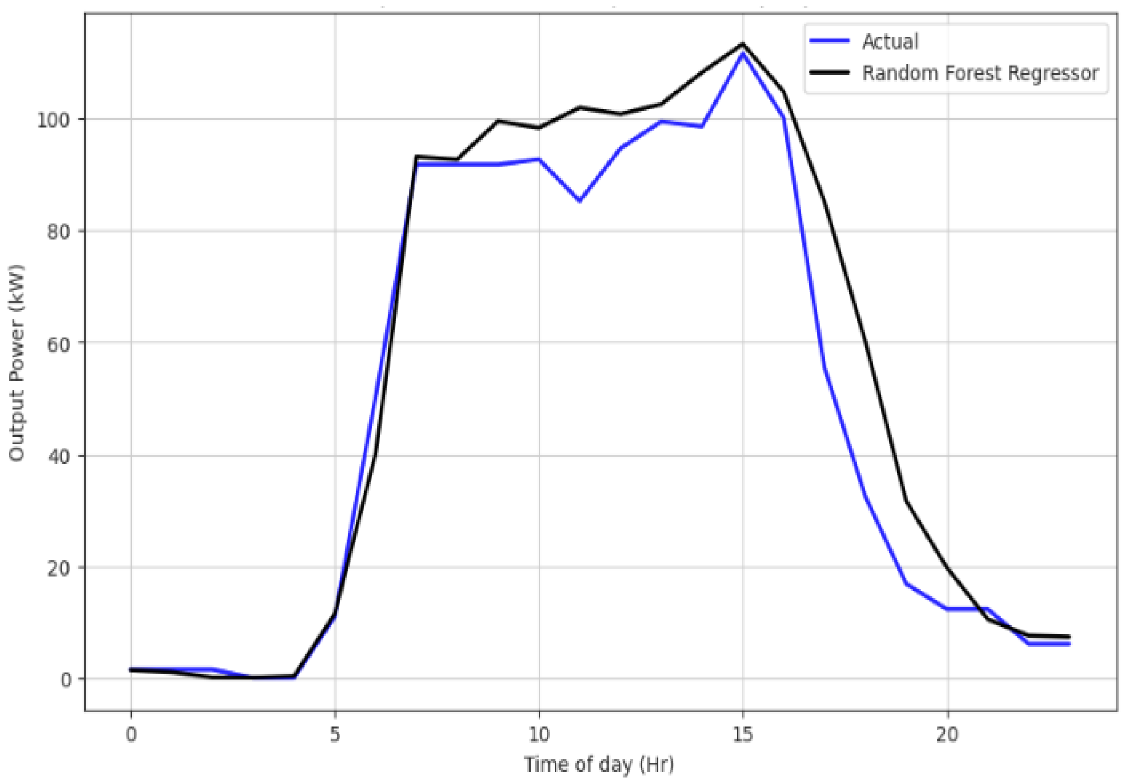

Figure 4.3 Random Forest Regressor model's energy prediction

The Random Forest model's prediction was more accurate than Prophet and LGB. The difference between the actual and the predicted values was negligible during the morning hours. Even during the later hours of the day, the forecast was much better than the other models. The performance metrics for Random Forest model are summarized in Table 4.3.

Metric	Value
MAE	6.45
RMSE	10.35

Table 4.3 Performance metrics for the Random Forest Regressor

4.1.4 Other Models Results

In addition to Prophet, LGB, and Random Forest Regressor algorithms, models such as ARIMA, SARIMA, and SARIMAX models were also applied to predict the energy consumption for the next day. However, these models performed poorly when compared to the other three algorithms. These models struggled to capture the data's seasonality and trends, resulting in poor predictions for the next day's energy consumption. Hence, these models were excluded from further analysis.

4.2 SOLAR FORECASTING

4.2.1 Goodness of Fit Test

The Goodness of Fit test performs to identify the most appropriate probability density function for the dataset. The statistical test considered Normal, Beta, and Weibull distributions. By performing this test, three statistical values are obtained that indicates the deviation of theoretical distribution from the distribution of the data set. The output of the statistical values should be the least for the best-fitted distribution. The test results for the dataset for a single hour are shown below:

```
Goodness-of-fit statistics
                                   beta      norm    weibull
Kolmogorov-Smirnov statistic 0.08126624 0.1041036 0.09252439
Cramer-von Mises statistic   0.19364507 0.2268069 0.20163889
Anderson-Darling statistic   1.25446175 1.2619030 1.26081377
```

Figure 4.4 Results of Goodness of Fit test for Solar irradiance

The results from Figure 4.4 conclude that the Beta distribution is the best-fitted distribution for solar irradiance. The shape parameters of Beta distribution for a segment of solar irradiance data are shown in Figure 4.5.

```
Fitting of the distribution ' beta ' by maximum likelihood
Parameters :
        estimate Std. Error
shape1 3.681489  0.4142684
shape2 4.171457  0.4731505
```

Figure 4.5 Shape parameters of Beta distribution for data set of one hour

A distribution object was created using the shape parameters to obtain the dataset's cumulative distribution function (CDF). A comparison between the three distributions for solar irradiance data set for a particular hour is shown in Figure 4.6.

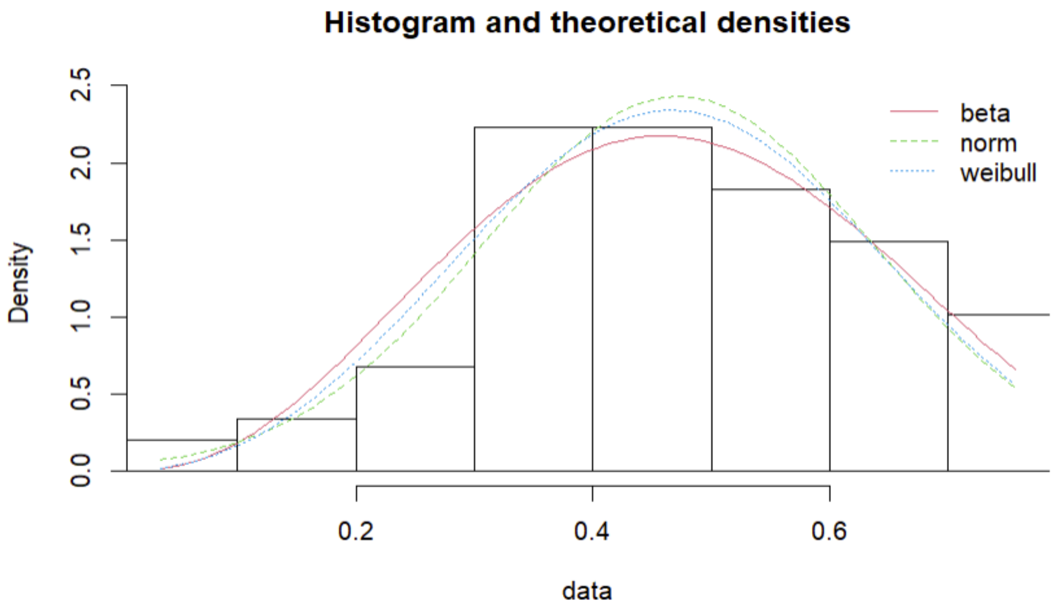

Figure 4.6 Comparison of distribution for solar irradiance

4.2.2 Forecasted Power Output of Solar

By performing the Goodness of Fit test, the Beta distribution is recognized as the best-fitted distribution for the data set. Thus, the shape parameters for the Beta distribution are identified for each hour segment. Using the shape parameters of the distribution, the distribution object for each segment was created, which helped in forming a cdf. Generating random data samples from the inverse cdf involved performing many iterations to obtain a uniform distribution. Hence, by using the values from Figure 4.5 along with the values of solar irradiance, the output power of the PV plant for each hour is identified. Section 3.2.1 discusses the equations for output power. Figure 4.7 depicts the output power of the PV plant obtained for each hour. The total capacity of PV is assumed to be 50% of the total energy demand from the forecasted energy demand in Section 4.1, which is equal to 54 kWh.

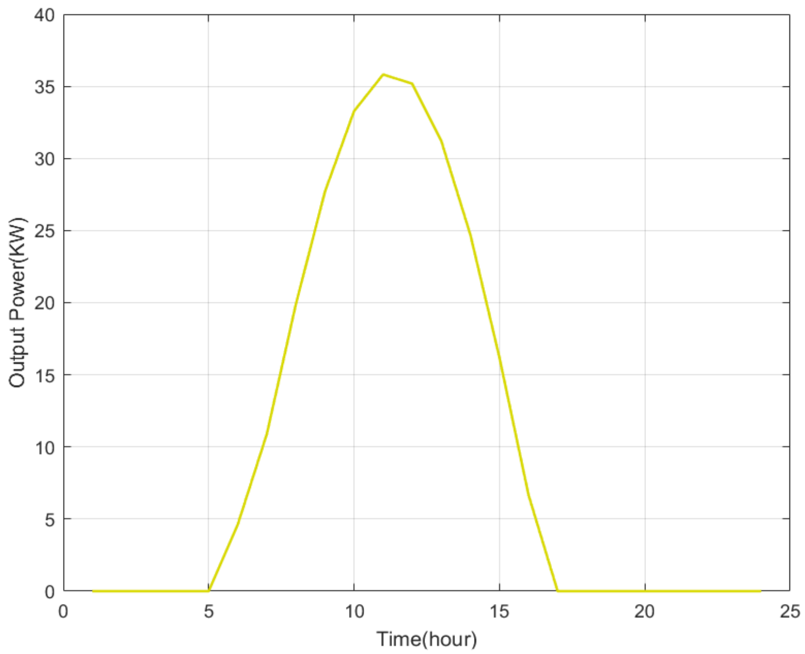

Figure 4.7 Variation of output power of PV plant with time

From Figure 4.7, it can be noticed that the output power of the PV plant is negligible before 5 am and after 4 pm. It is because there is less sunlight in the evening and no sunlight at night. Hence the power output is negligible. Furthermore, the PV power output reaches its maximum value around 10 am and remains almost constant till noon. It is because of the high amount of sunlight during mid-day. These observations it verifies that the predicted output power of PV resembles the actual power output from PV in a day.

4.3 OPTIMAL SCHEDULING

Two different case studies are analysed. In the first case study, only a single power rating (3kW) for charging is considered. In the second case study, slow and fast charging are considered for analysis and presented in Table 4.4. In case two, there is a limit on the number of stations for each power rating which is also presented in Table 4.4. In both the cases, the analysis is carried out as follows: (i) Uncontrolled charging, (ii) Controlled charging without a PV power source, and (iii) Controlled charging with a PV power source.

Type of Charging	Charging Power	Number of Stations
Slow Charging	3 kW	30
Fast Charging I	7 kW	20
Fast Charging II	11 kW	10

Table 4.4 Types of Charging Stations

4.3.1 Synthesizing Data

The Goodness of Fit test identifies the most appropriate distribution for arrival, departure, and energy required. Multiple distributions were evaluated for statistical tests. For each data, different distributions were recognized to be best fitting. Figures 4.8, 4.9, and 4.10 illustrate each data's statistical test results.

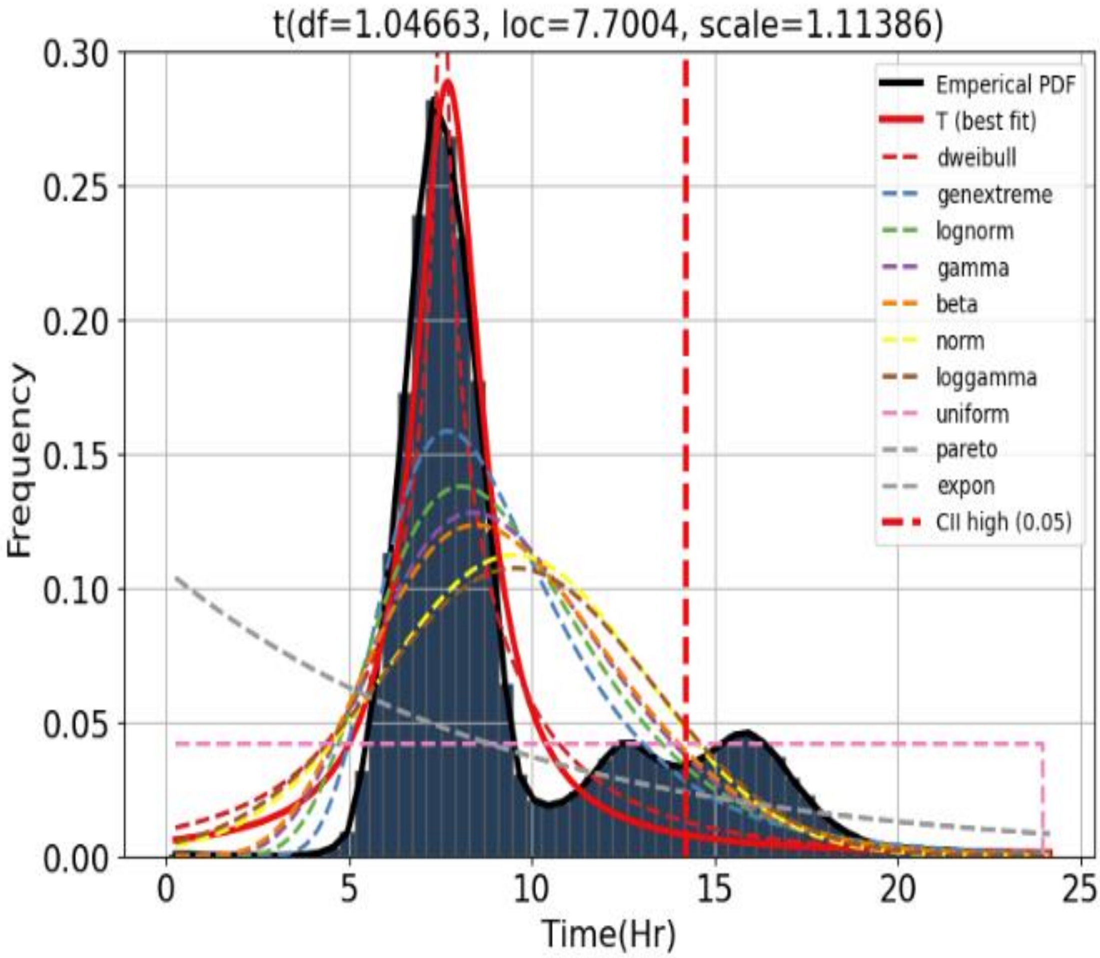

Figure 4.8 Probability distribution functions for Arrival time

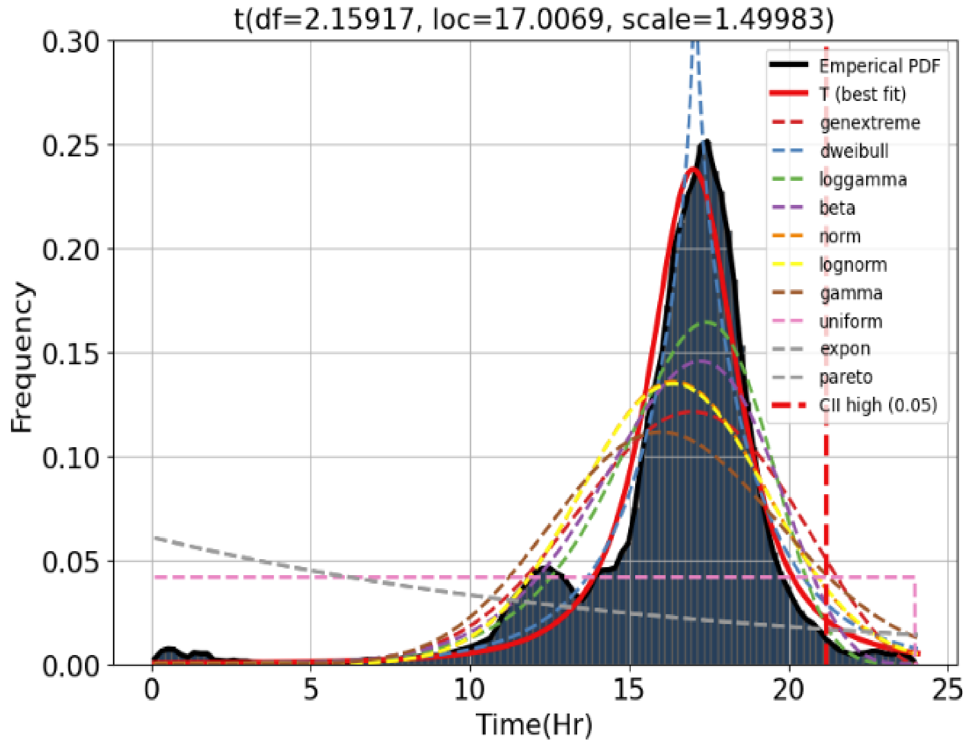

Figure 4.9 Probability distribution functions for Departure time

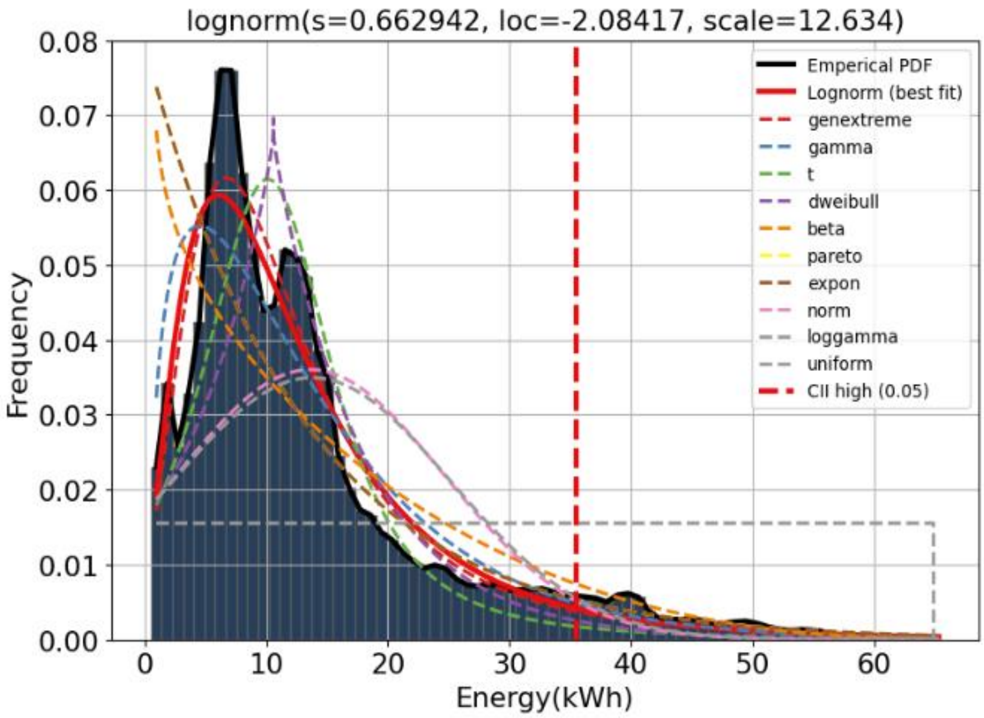

Figure 4.10 Probability distribution functions for Energy required

T-distribution is the best-fitting distributions for arrival time, and departure time as seen in Figures 4.8, 4.9. Log-Normal distribution is the best-fitting distributions for energy required as seen in Figures 4.10. Equation 3.7 is evaluated to identify the number of data to synthesize by utilizing the total energy demanded and synthesized data from the energy required. The evaluation reveals the count of vehicles as 77. Later, using the identified values, data is synthesized for arrival, departure, and energy required. Table 4.5 shows a sample of synthesized data.

User Id	Arrival time	Departure time	Energy required (kWh)
User_1	6:21:23 AM	10:08:58 AM	11.14
User_2	7:21:05 AM	12:05:25 PM	26.4
User_3	3:07:04 PM	10:56:22 PM	15.16

Table 4.5 Sample User data

4.3.2 Optimizing EV Charging Schedule with Single Charging Rate

For the first case, only slow charging was considered for all the available stations, and the number of stations was not considered. It is assumed that enough stations are available to accommodate the cars arriving for charging at any time. Hence, whenever a new car arrives, it is directed toward charging without considering the station's availability.

There are three input data for scheduling: the arrival, departure time, and energy required. The arrival and departure times are when a new vehicle arrives and leaves the charging station. The energy required is the total amount of energy demanded by the vehicle. Table 4.6 shows a few vehicles' input data and charging times.

User Id	Arrival time	Departure time	Energy required (kWh)	Charging time at 3kW	Charging time at 7kW
User_1	6:21:23 AM	10:08:58 AM	11.14	3:42:47	1:35:29
User_2	7:21:05 AM	12:05:25 PM	26.4	8:47:55	3:46:15
User_3	3:07:04 PM	10:56:22 PM	15.16	5:03:15	2:09:58

Table 4.6 Sample Input data with Charging duration

The input data is passed into the algorithm, which does the entire scheduling as mentioned in section 3.3. Three further analysis is carried out, namely, uncontrolled charging, controlled charging without a PV power source, and controlled charging with a PV power source. The result of three analyses on User_2 (mentioned in Table 4.5) is depicted in Figure 4.11.

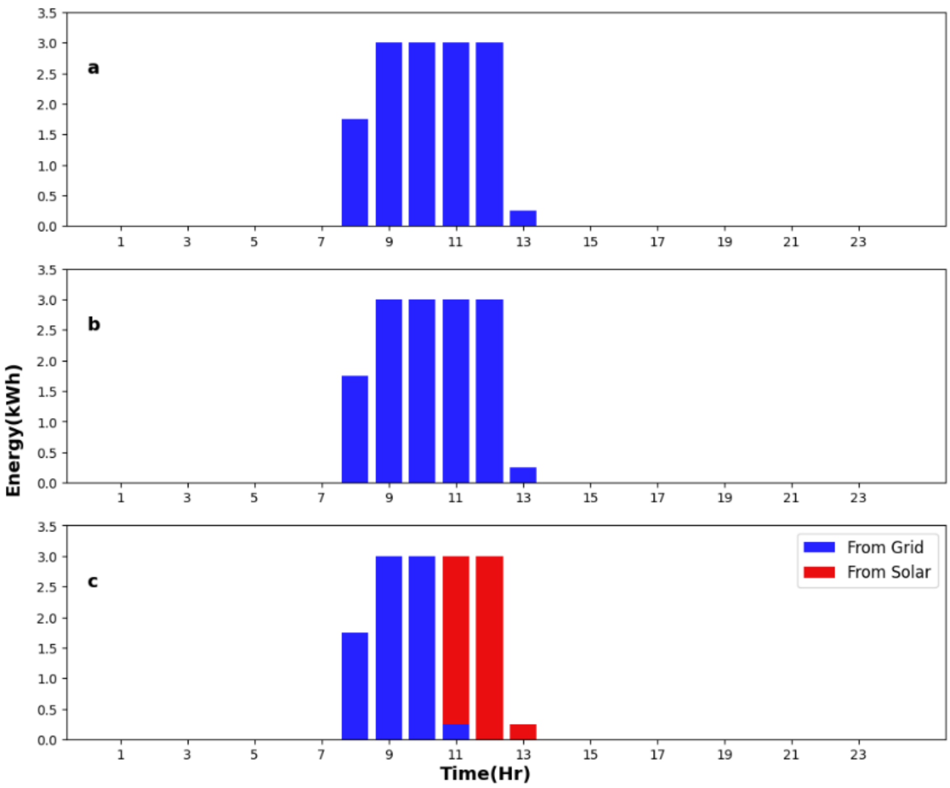

Figure 4.11 Energy delivered with single charging rate (a) Uncontrolled charging (b) Controlled charging without PV power (c) Controlled charging with PV power.

From Figure 4.11, it is noticeable that the graph looks the same in the analysis of Controlled charging without PV power and Uncontrolled charging. It is because the energy demanded by User_2 is high, and the vehicle should be charged for the entire duration to meet a part of its demand. However, in Controlled charging with PV power, the same energy is supplied partly with PV power. The red color in the plot indicates the time slot during which the vehicle was charged using a PV power source. The vehicle (User_2) uses PV power only during specific time slots since the available PV power during other time slots is almost negligible. It is because of the previously arrived vehicles that have already been scheduled to charge using PV power during the other slots. Hence, the vehicle (User_2) charges when there is enough PV power during the time slots. The charging cost for the vehicle in all different analyses is depicted in Figure 4.12.

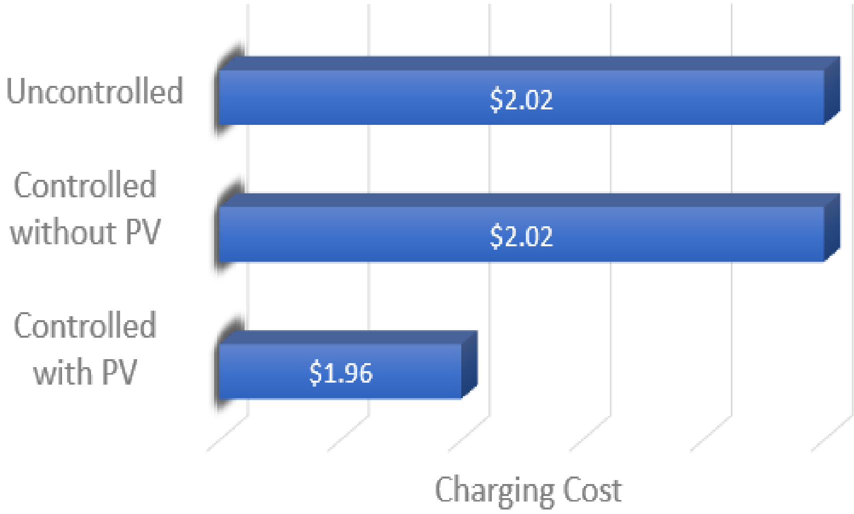

Figure 4.12 Charging cost with single charging rate

From Figure 4.12 cost of charging through Uncontrolled and Controlled without PV power is identical for the vehicle. Nevertheless, it will vary for vehicles with different user inputs. However, through Controlled charging with PV, charging costs are reduced by 3%. Multiple cars are charged daily in the charging station, so the summation of all costs is depicted in Table 4.7. Through Controlled charging without PV, users can save 9.6% compared to uncontrolled charging. Similarly, through controlled charging with PV, the users can save 17.5% compared to uncontrolled charging.

Analysis	Cost
Uncontrolled charging	$137.26
Controlled charging without PV	$124.08
Controlled charging with PV	$113.20

Table 4.7 Cost involved in different analysis with single charging rate.

The analysis of controlled charging with PV involves two costs. The former is the cost involved in taking power from the grid. The latter is the cost of sending power from PV cells back to the grid. The power is sent back to the grid when excess power is generated from the PV panel, which is not utilized by any vehicles. Through this method, the station can earn excess profit. Different costs involved in controlled charging with PV are depicted in Table 4.8. As money is earned when power is returned to the grid, it is indicated as a negative value in Table 4.8.

Type of charging	Cost
From Grid	\$115.37
To Grid	-\$2.17

Table 4.8 Controlled charging with PV costs (Single charging rate).

4.3.3 Optimizing EV Charging Schedule with Multiple Charging Rates

Unlike the first case, in this case, there are multiple charging stations with charging rates of 3kW, 7kW, and 11kW with a limited number of stations, as mentioned in Table 4.4. Like the previous case, details such as arrival time, departure time, and energy required are considered for scheduling. An assumption is made for this case that all the vehicles arriving at the station would be capable of charging at all the different rates without any issue. Like the previous case, three different analysis is carried out. The result of three analyses on User_2 (mentioned in Table 4.5) is depicted in Figure 4.13.

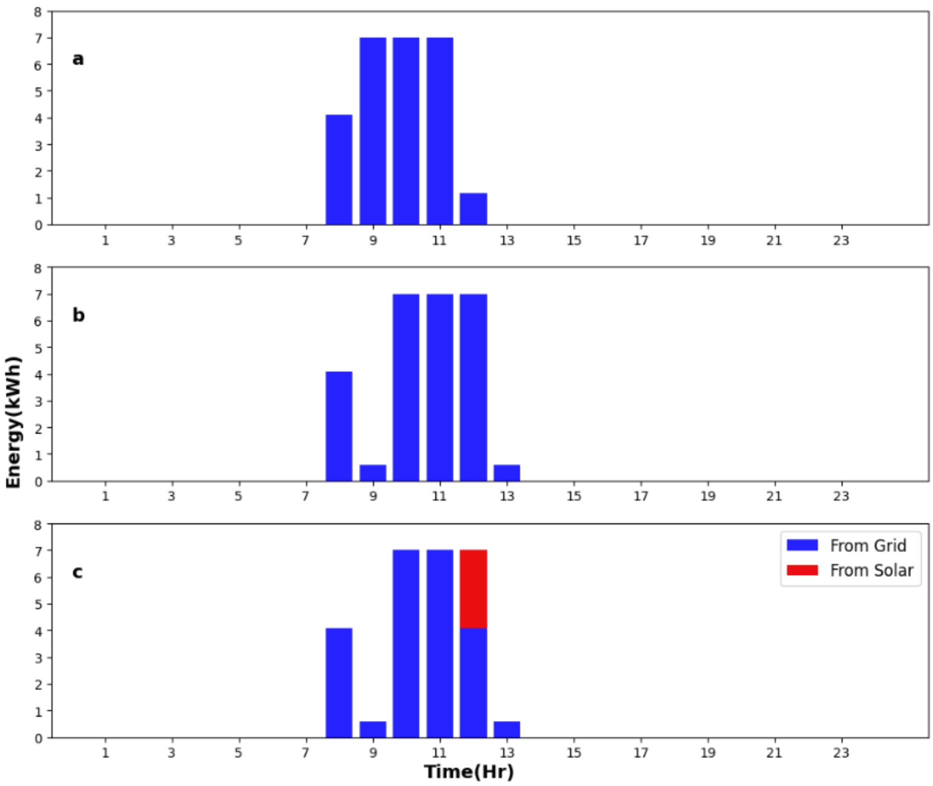

Figure 4.13 Energy delivered with multiple charging rate (a) Uncontrolled charging (b) Controlled charging without PV power (c) Controlled charging with PV power.

Figure 4.13 shows that vehicle (User_2) utilizes Fast Charging I as the type of charging. It is because the amount of energy demanded by the vehicle is high and cannot be delivered with slow charging before the departure time. Hence, the algorithm chooses Fast Charging I to deliver the energy demanded.

As there is PV power available at later hours, the algorithm decides to charge the vehicle using PV power instead of grid power. However, during some hours, the energy supplied is lesser because vehicles that arrive earlier have already been assigned to use PV power during that time slot. Hence, the algorithm chooses the time slots when PV power is available to charge the vehicle (User_2) before its departure time. The charging cost for the vehicle in all different analyses is depicted in Figure 4.14.

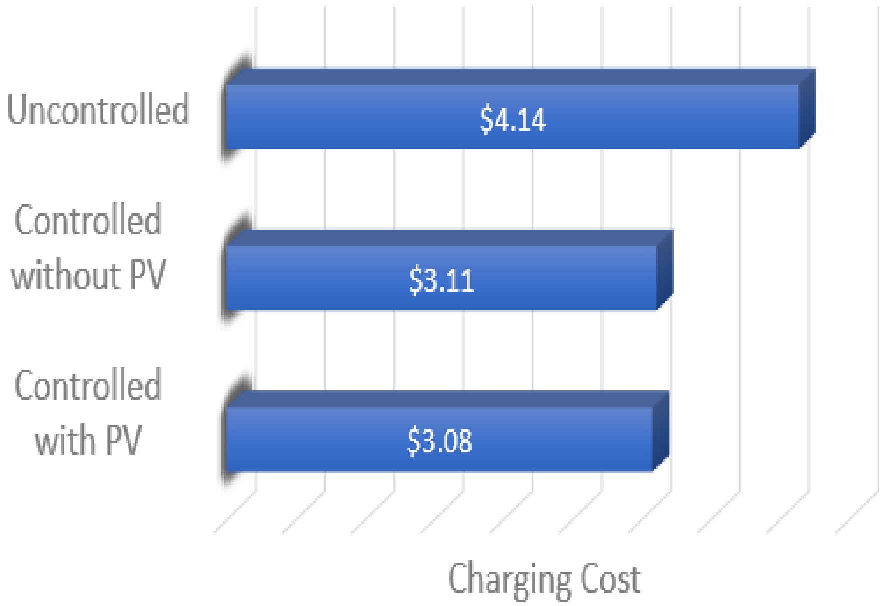

Figure 4.14 Charging cost with multiple charging rate

From Figure 4.14, through Controlled charging without PV, charging cost is reduced by 24.8% compared to Uncontrolled charging. Similarly, through Controlled charging with PV, charging costs are reduced by 25.6%.

Multiple cars are charged daily in the charging station, so the summation of all costs is depicted in Table 4.9. Through Controlled charging without PV, the users can save 22.5% compared to uncontrolled charging. Similarly, the users can save 26.4% through controlled charging with PV.

Analysis	Cost
Uncontrolled charging	$164.79
Controlled charging without PV	$127.71
Controlled charging with PV	$121.21

Table 4.9 Cost involved in different analysis with multiple charging rate.

As mentioned in section 4.3.1, the analysis of controlled charging with PV involves two costs: the cost involved in taking power from the grid and the cost involved in sending excess power back to the grid. In the latter method, the station earns excess profit. Different costs involved in controlled charging with PV are depicted in Table 4.10.

Type of charging	Cost
From Grid	$123.29
To Grid	-$2.07

Table 4.10 Controlled charging with PV costs (Multiple charging rate).

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 CONCLUSION

This thesis implements a scheduling algorithm to reduce electric vehicles' charging costs and minimize the negative impact on the power grid. Two case studies were analyzed with single and multiple charging rates. In each case, three analyses: uncontrolled, controlled without PV, and controlled with PV, were analyzed by comparing the charging cost. The study reveals that with a single charging rate, the charging cost is reduced by 17.5%, and with multiple charging rates, the charging cost is reduced by 26.4%. The analysis shows that through a single charging rate, the charging station reduces the charging cost by $24.06, and through multiple charging rates, the charging station reduces the charging cost by $43.58. The cost saved is an analysis performed daily for controlled charging with PV systems. The cost saved in multiple charging rates is higher because all energy demanded is delivered. Since with a single charging rate, in a few scenarios, as the charging duration is less, the demanded energy could not be delivered within the departure time. From the results and analysis, it is concluded that optimal scheduling reduces the charging cost compared to an uncontrolled approach. Additionally, integrating PV power with the scheduling algorithm enhances the sustainability and cost efficiency of EV charging.

5.2 FUTURE SCOPE

- The proposed algorithm can be implemented in a real-world setting to evaluate its performance under different conditions, such as varying weather conditions or traffic patterns.
- The algorithm can be integrated with advanced energy management systems that consider the charging cost and the power grid's overall stability.
- The forecasting of energy demand can be improved by fine-tuning the results.
- Forecasting of the output power of PV can be improved by implementing machine learning-based techniques.

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