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# Smart EV Charging for Improved Sustainable Mobility

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# SMART EV CHARGING FOR IMPROVED SUSTAINABLE MOBILITY

A thesis submitted in partial fulfillment of the
requirements for the degree of
Master of Science in Computer Engineering

By

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I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY **Ashutosh Shivakumar** ENTITLED **Smart EV Charging for Improved Sustainable Mobility** BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Master of Science in Computer Engineering.

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# ABSTRACT

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The landscape of energy generation and utilization is witnessing an unprecedented change. We are at the threshold of a major shift in electricity generation from utilization of conventional sources of energy like coal to sustainable and renewable sources of energy like solar and wind. On the other hand, electricity consumption, especially in the field of transportation, due to advancements in the field of battery research and exponential technologies like vehicle telematics, is seeing a shift from carbon based to Lithium based fuel. Encouraged by 1. Decrease in the cost of Li – ion based batteries 2. Breakthroughs in battery chemistry research - resulting in increased drive range 3. Government incentives and tariff concessions by utilities for EV owners in the form of tax credits, EV – only parking spaces, free charging equipment etc., the automobile market, especially the passenger vehicle market, is witnessing a steady growth in the sale of electric vehicles. This has resulted in Electric Vehicles contributing to the electricity load resulting in two challenges 1. At the supply end, it contributes as a potential micro energy storage system to fit the time gap between the demand for electricity and the supply of renewable and/or low cost electricity generation; and, 2. At the consumer-end, it creates a necessity to make energy consumption as sustainable and renewable as possible, while preserving battery life.

In this thesis work we attempt to provide multiple practical solutions to address these needs by advancing existing technologies in the industry. Firstly, we have developed a “Joint EV-Grid Solution for Robust and Low-Complexity Smart Charing”, where we have designed and implemented a distributed smart charging algorithm, which runs in the EV with load and pricing information collected from Grid through the charging station. It is responsible for optimizing the charge plan of the user’s vehicle based on his/her preference and ensure a full charge before departure. The objective could be minimizing the electricity cost per charge session or maximizing the renewable energy usage. For instance, by setting the preference to optimize the algorithm according to “Price”, the additional demand is scheduled to off-peak hours (i.e., incurring the least cost). Alternatively, by setting the preference to “Renewables” the EV charges based on the maximum availability of renewable energy sources, thereby maximizing the utilization of renewable energy resources which may lead to reduced cost, if not minimize it.

Furthermore, we have improved on our initial approach by introducing “Smart Charging Solution through Usage/Charging Pattern Learning” where we have used machine learning algorithms like Logistic regression and Fuzzy Logic to enable EVs to learn the usage and charging pattern of users and prepare a charging plan that is personalized at the users’ end and prevents potential smart-changing-caused demand peaks by distributing the net load throughout the day.

Through our experiment studies we were successful in creating a distributed Charging algorithm and a Machine Learning system that could cater to the said requirements through innovative charging strategies. Consequently, helping us create a sustainable, win – win situation for both electricity consumer and producer.

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Last but not the least, my parents, for being my backbone throughout this journey.

# Chapter 1. Introduction

## 1.1 Current Electric Vehicle Trends

Electric energy consumption and generation is witnessing an unprecedented change. There is a shift in electricity generation from utilization of conventional sources of energy like coal to sustainable and renewable sources of energy like solar and wind. On the other hand, energy consumption, especially in the field of transportation, due to advancements in the field of battery research and exponential technologies like vehicle telematics, is seeing a shift from petroleum based to electricity based fuel.

In recent years, the automotive market, especially the passenger vehicle market, is witnessing a steady growth in the sale of electric vehicles. Particularly, consumers in states like California, the biggest automotive market in the USA, are among the earlier adopters of Electric vehicles for transportation[1]. EVs are expected to become one of the major automobiles in the USA and worldwide as shown in Figure 1.1[2].

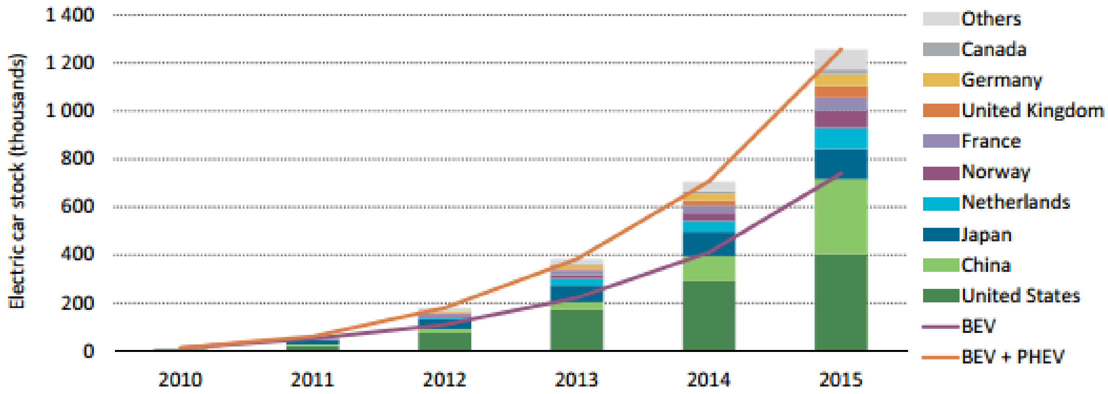


**Figure 1.1 Worldwide Electric and Hybrid vehicle adoption since 2010**

The following reasons explain this trend:

1. Decrease in battery costs leading to affordable electric cars[3], [4].
2. Breakthroughs in Li – ion battery chemistry research (e.g., high energy density of Lithium anode) - resulting in increased drive range[5].
3. Rapid expansion of fast charging station network.
4. Entry of major automobile manufacturers like General Motors, BMW, Ford, Honda, Toyota etc. into the EV market.
5. Increased vehicle durability due to lesser number of moving parts used in manufacturing[6].
6. Government incentives and tariff concessions by utilities for EV owners in the form of tax credits, EV – only parking spaces, free charging equipment etc.[7].

This has resulted in Electric Vehicles contributing to the electricity load resulting in two new challenges: 1. EV charging demands significant increase in electricity consumption at home, which may worsen the already-stressful peak-to-average demand pattern in the Grid as evident in the Duck curve shown in Figure 1.1; and, 2. At the consumer-end, it creates a necessity to make energy consumption as sustainable and renewable as possible, while preserving battery life.

Hence, through this thesis work we attempt to provide multiple practical solutions to these problems using existing technologies in the industry.

## 1.2 Motivation

We list the motivating factors for this thesis work in the following section.

### 1.2.1 Government regulations and international treaties

To reduce the harmful carbon emissions due to burning of fossil fuels. Fossil fuels that are the primary cause for climate change and as per the Paris Climate Agreement that came into force on 4$^{th}$ November 2016 and ratified by 144[8], [9] countries of the world, have proposed to prevent the global average temperature not more than 2 degree Celsius[8]. This requires all regulations and policy to comply with the 100% clean energy objective[10].

In addition to the "Paris Agreement" states within the US namely, California, Connecticut, Rhode Island, Oregon, New York, New Jersey, Oregon, Rhode Island, Maine, Maryland, Massachusetts and Vermont follow a California state regulation called 'ZEV' (Zero Emission Vehicle) program that mandates all automotive manufacturers to market, develop and research electric vehicles that generate fewer global warming emissions[11]. Further, countries like China and Europe have started programs for widespread integration of renewable energy resources into their power grid and subsidies for Electric Vehicle consumers.

These regulations have necessitated automotive manufacturers and utilities across the world to find ways to collaborate to meet the respective emission goals set by the governments. This has given rise to an increase in the financial outlay towards research and development for innovative technologies like Li-ion batteries and standardization of Vehicle to Grid communication protocols like ISO 15118. It has also led to the entry of 'Home Energy Management' systems that use batteries to store excess electric energy derived from solar/wind energy, or being charged at the valley of duck curve; and then use it to meet the energy needs of the people at peak hours.

Since the above stated technologies play an important role in charging of EVs, there is a strong need for seamless integration of these technologies to make the charging process economical, renewable and sustainable.

### 1.2.2 Load Management

Load management also known as 'Demand Side Management' is a process in which utilities balance the supply-demand of electricity by using special tariffs to influence customer usage. This allows utilities to reduce demand during periods of peak usage by encouraging customers to charge during off-peak times by reducing the tariffs[12].

Figure 1.2 represents the net load curve. This net load is necessary for the utilities to make decisions on the generation capacity. For our case study, we have used the duck – curve representation of net - load of the state of California, USA as shown in Figure 1.2.

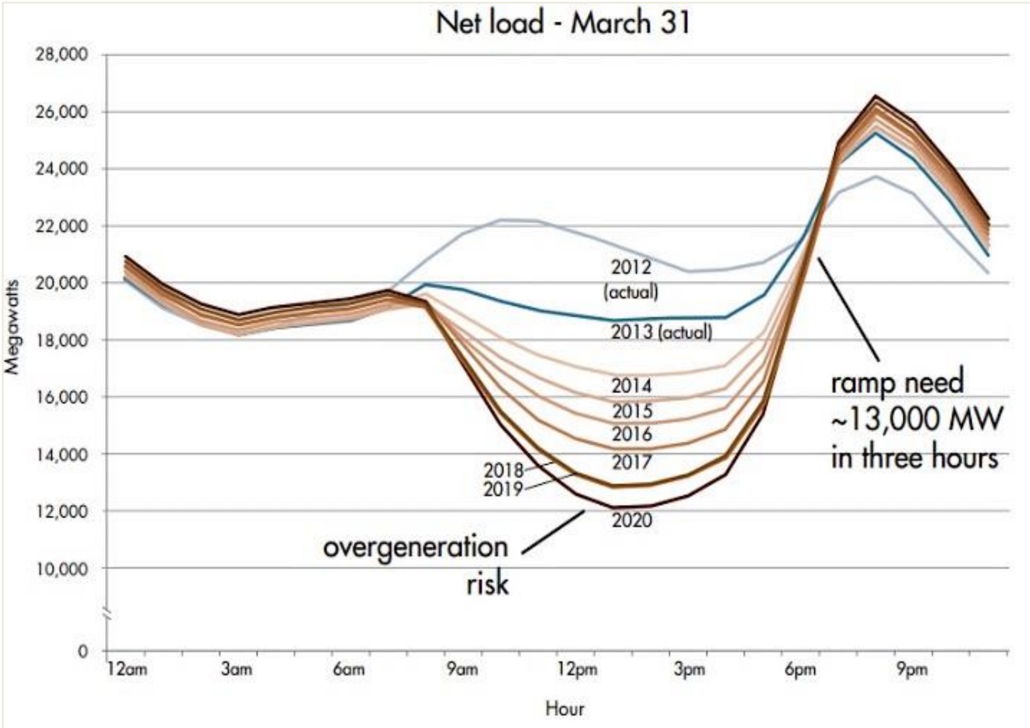


**Figure 1.2 California Duck – Curve (Courtesy: California ISO)**

From the Figure 1.2 [13], we infer that there is a sharp ramp of demand from 3:30 pm to 7:30 pm leading into a peak at 8:00pm. The depth of this ramp increases with each passing year due to the increase in the integration of renewable resources. This integration during late afternoon reduces the need for drawing power from the grid. However, as the day grows into early evening, there is a strong demand of electricity as majority of the people return from work and turn-on appliances at homes. If electric – vehicles charge during this period they act as additional load to the grid, thereby contributing to the stress on the distribution transformers.

Hence, there is a benefit for both the Grid and household to ensure charging of electric vehicles during off-peak times to reduce the burden on grid and lower the cost to the consumer.

### 1.2.3 Cheaper Energy Consumption

One of the most important motivating factors for introducing smart – charging technology for charging EVs is to reduce the cost of energy consumption to the end user. The source of energy for electricity generation today is dominated by natural gas and coal. The usage of these fuel types contributes to the cost of charging and environmental pollution. The use of a level – 2 (240V) AC charging station contributes to the total household energy consumption. This cost of EV charging increases considerably during periods of peak energy consumption. Additionally, if we expand EV transportation to large service sector vehicles like mail – delivery vans, buses and trucks the cost of charging these vehicles with larger batteries will increase even more. To get a perspective on the scale and cost of charging, consider the following example:

Example: Let us assume a commuter must cover 50 miles every day and let cost per mile of the vehicle is 0.23 USD (including fuel, tires, maintenance and registration) [14]. On scaling this to a year the cost increases to about $4200 USD for a single vehicle. It is a significant expense. Hence, there is a need to reduce the price of charging on electric vehicles so that the money saved can be used for other household needs.

### 1.2.4 Personalization

In today's world, there is strong demand for personalization of goods and services. Personalization contributes accurately to the needs of people. This increases user – convenience. We believe EV charging is no different and envision a charging system where an EV owner can choose between 'Renewable - Friendly' or 'Cost – Effective' modes of charging. When the charging preference is set to 'Renewable - Friendly' mode, the vehicle charges during presence of high availability of solar energy; similarly, if ‘Cost – Effective’ charging mode is chosen, the preference is given to charge according to the time of day, representing the minimum cost of power. Customer preference could change based on their requirement and available charging facilities (Ex: Presence or absence of Home Energy management system). Hence, in an actual implementation it is important that we provide the customers with the choice of charging based on their needs.

### 1.2.5 Conformation to a Fully - Autonomous Future

Presently, we are witnessing an increased impetus given to application of Artificial Intelligence in development of technologies. This has led to creation of automobile driving platforms like Autonomous driving, which seek to increase safety and reduce the burden of driving. The extension of this concept to EV charging, where the electric vehicle learns from the driving profile of the user, results in: 1. User convenience: where the user does not have to worry about charging, as the vehicle autonomously takes care, based on learnt user - profile. 2. Prolongation of the EV battery life, by preventing over – charging or unnecessarily-frequent charging [15].

## 1.3 Our Solution

Through this thesis work, we propose two smart charging solutions with increasing learning capabilities to address the issues discussed in the previous section:

### 1.3.1 A Joint EV-Grid Solution for Robust and Low-Complexity Smart Charing

We have designed and implemented a distributed smart charging algorithm, which runs in the EV with load and pricing information collected from Grid through the charging station. It is responsible for optimizing the charge plan of the user's vehicle based on his/her preference and ensure a full charge before departure. The objective could be minimizing the electricity cost per charge session or maximizing the renewable energy usage. For instance, by setting the preference to optimize the algorithm according to "Price", the additional demand is scheduled to off-peak hours (i.e., incurring the least cost). Alternatively, by setting the preference to "Renewables" the EV charges based on the maximum availability of renewable energy sources, thereby maximizing the utilization of renewable energy resources which may lead to reduced cost, if not minimize it.

However, it should be noted that as cost of electricity is decided corresponding to the demand, all vehicles might charge at those periods of time when the demand for power is minimum. This leads to change of Grid demand pattern, which must be correctly predicted to produce robust charging plan. Due to the limited information, available at each individual EV, it is difficult to produce such prediction reliably and accurately.

In a way, similar to a hybrid Mobile and Cloud system, such as Google Earth, in this project, we explore the load prediction capabilities that is already made available by the Grid to reduce the complexity at the EV's on-board charging unit. In addition, the grid, with the most complete information about the usage, can produce the load prediction more accurately and faster. We will exam the robustness of our charging algorithm by producing charging plan based on predicted load data received from the Grid through a cellular link.

Particularly, the smart charging algorithm running on the Electronic Control Unit (ECU) in the EV, receives information pertaining to the day-ahead or hour-ahead predicted demand, the two load predictions currently made available by the Grid. In addition, the

Grid may also provide information about availability of renewable resource. The communication between charging station and EV is governed by the high-level client-server charging protocol ISO 15118, which is currently under development. The charging station in turn receives this information from the database of the Utilities (i.e., Grid) via a cellular link.

To prove the viability of the smart charging algorithm and analyze the economic benefits of integration of Home Energy Storage systems into the charging mechanism, we have considered the following two cases: **1.** Charging of EVs by considering the price curve, corresponding to the energy demand **2.** Charging EVs by considering the availability of renewable energy from the home energy system along with the price curve. Furthermore, we analyze these two cases in the following charging strategies: **1.** Regular charging without optimization (i.e., plug in and charge); **2.** Regular charging but with reduced charging rate, e.g., at half power; **3.** EV charging by using the smart charging algorithm. We use these methods to understand the benefits of smart – charging over normal charging at full and half – rate of power transfer.

Moreover, we will examine the robustness of the smart charging algorithm by evaluating the amount of cost benefit attained even if no perfect load information is available. Thus, the total cost of charging will be compared when the charging schedule is produced based on*:* **1.** Actual demand curve from the utility. **2.** Hour-ahead prediction demand curve; and, **3.** Day-ahead prediction of demand curve. Intuitively, the charging schedule based on the actual demand curve will produce the minimal cost; however, it is not possible to predict it perfectly in practice. The hour-ahead and day-ahead predictions, on the other hand, provide a realistic way to obtain the load information; but prediction error may lead to the mismatch, and result in sub-optimal solutions. Our goal is to investigate the robustness and accuracy of using the day-ahead and hour-ahead predictions and its impact on the actual cost. If the charging cost based on day-ahead and hour-ahead predictions are not significantly more than the actual one, we demonstrate that charging decisions can be made in advance, e.g., by a day, giving the user, an estimate of his energy costs and the utilities an approximation of the total load. It will help us validate the achievable benefit of smart charging in the real-world operations.

### 1.3.2 An improved Smart Charging Solution through Usage/Charging Pattern Learning

In a future dominated by various applications of artificial intelligence in our daily driving habits, we envision a user-friendly EV, that can make charging decisions on behalf of the owner/driver according to his/her usage and charging behavior, and make itself adequately charged for the owner/driver to begin driving at the time of departure. It is important to prevent the electric vehicle from overcharging to preserve the durability of the battery. This can be accomplished by logging the owner/user’s charging data and classifying it to a user-profile class, based on various usage/charging patterns, and preparing a charging schedule for the same.

Hence, through this approach, we explore machine-learning paradigms, namely, Fuzzy-logic and Logistic Regression in this thesis, to build these decision-making capabilities into the car and make the whole charging process devoid of human interference.

# Chapter 2. A Joint EV-Grid Solution for Robust and Low-Complexity Smart Charing

In this chapter, we propose a grid-assisted EV smart charging algorithm. The proposed algorithm has the following features:

1. To shift the EV charging to off – peak time.
2. Integration of renewable energy, e.g., stored in the batteries of the Home Energy Management system.

In this chapter, we present a detailed description of the algorithm, a system architecture and explain the results of the localized optimization algorithm approach to smart charging of Electric Vehicles.

## 2.1 System Description

### 2.1.1 Information Source for Load Data

All information pertaining to the predicted and actual load is inferred from the California ISO database [16].

### 2.1.2 Assumptions

We make the following assumptions for algorithm implementation:

**1.** Total EV battery storage: 30kWh

**2.** Full charging rate: 7kW for a 240V level 2 charging station.

**3.** Half charging rate: 3kW for a 240V level 2 charging station.

**4.** We assume the total power transmitted from the charging station and received by the EV are equal. We neglect the power loss due to resistance, capacitance and inductance of the intermediate circuitry.

### 2.1.3 Algorithm Description

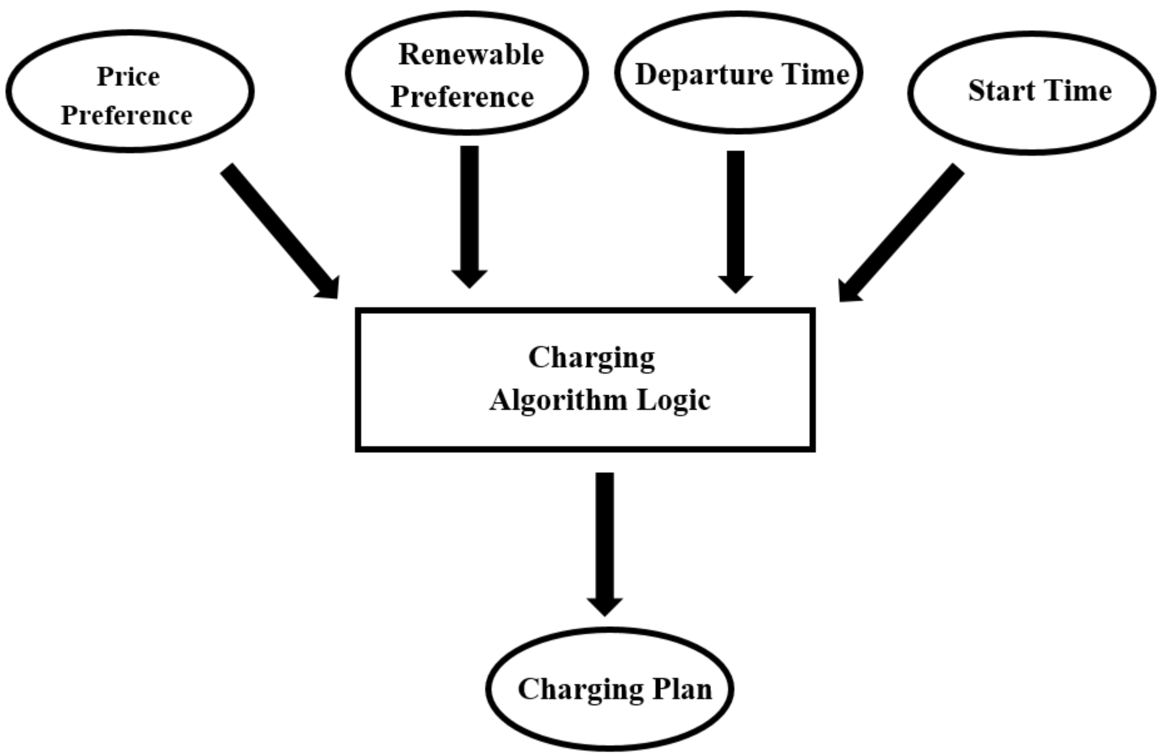


**Figure 2.1 Smart – Charging Logical View**

The above diagram represents the logical view of the smart charging algorithm. The description of each term associated with this algorithm is found in Section 2.1.3.1.

#### 2.1.3.1 Input parameters

##### 2.1.3.1.1 Price preference (%):

It represents one of the choice used by the customer to optimize the charging schedule. "Cost of charging" is predicted on a day-ahead or hour-ahead basis as per demand information from the public utility commission. The charging plan is prepared according to this predicted data, but the actual cost has to be calculated based on the real demand which may be different from the prediction. The outcome also reflects the robustness of the charging algorithm to such disparity.

By setting a "Price" preference of 100 percent would enable the EV to optimize the charging algorithm to prepare a charging plan corresponding to minimum cost of charging.

##### 2.1.3.1.2 Renewable preference (%):

It denotes the criteria used by the customer to optimize the charging algorithm as per "maximum availability of renewable energy" parameter. "Maximum availability of renewable energy" is the day-ahead or hour-ahead prediction. The cost for the same is calculated based on the renewable energy service provider (Example. The solar panel or the home energy system leasing entity).

Example: Setting a price preference of 100 percent would enable the EV to optimize the charging algorithm to prepare a charging plan corresponding to the time of day corresponding to the maximum availability of solar energy.

Note: Provisions have been made in the algorithm for customers to set a combination of the two preferences.

Example: Setting a price preference of 60 percent and 40 percent for renewables would enable the EV to optimize the charging algorithm to prepare a charging plan corresponding to the respective proportion “Maximum availability of renewable energy” and “Price preference”.

#### 2.1.3.1.3 Arrival Time or start time (HH:MM):

It is the time at which the charging session begins for the Electric vehicle. The start time, for the sake of demonstration, at present, can be set at the beginning of one full hour (Ex: 06:00, 16:00 etc.)

#### 2.1.3.1.4 Departure Time (HH:MM):

It is the time at which the charging session ends for the electric vehicle. It represents the hard deadline by which the EV must stop charging. The departure time, for the sake of demonstration, at present, can be set at the beginning of one full hour (Ex: 06:00, 16:00 etc.) and should always be after the “start time”.

#### 2.1.3.1.5 Present State of Charge (%):

It represents the percentage of energy in the battery of the EV at that instant of time. The algorithm prepares cost and/or renewable optimized charging schedule to add the remaining percentage of energy to the battery.

Ex: 60% SOC means, the battery has 60% of total energy that can be stored by the EV, at that instant of time. Hence, the algorithm prepares a charging plan for the remaining 40% of battery capacity to be filled by the departure time.

#### 2.1.3.2 Output parameters

##### 2.1.3.2.1 Charging Plan

It is a data structure, represented by a file or a two-dimensional array sent by the EV to the charging station that depicts the charging plan in the form of energy requirements in kWh (kilowatt hour) at each instant of time from the beginning of each full hour. The charging plan is optimized to transmit the maximum electrical energy before the departure time for minimum cost and/or maximum availability of renewable energy based on the customer preference. It is calculated, based on the day or hour-ahead prediction of electrical energy demand in the form of cost and/or availability of renewable energy.

Example:

**Table 2.1 Sample charging plan**

| TimeStamp | DayAheadPredictionPrice | Actual Cost | Renewable | Plan |
|---|---|---|---|---|
| 06:00 | 10.76 | 11.48 | 0 | 0 |
| 07:00 | 12.16 | 12.64 | 0 | 0 |
| 08:00 | 13.1 | 12.94 | 0.52 | 0 |
| 09:00 | 13.24 | 13.2 | 1.65 | 0 |
| 10:00 | 13.19 | 13.29 | 2.47 | 7 |
| 11:00 | 13.01 | 13.16 | 2.66 | 7 |
| 12:00 | 12.82 | 12.98 | 2.89 | 7 |
| 13:00 | 12.73 | 13.05 | 2.86 | 7 |
| 14:00 | 12.73 | 12.78 | 2.47 | 7 |
| 15:00 | 12.73 | 13.15 | 1.79 | 0 |
| 16:00 | 12.81 | 13.32 | 0.74 | 0 |
| 17:00 | 13.4 | 14.62 | 0 | 0 |
| 18:00 | 14.9 | 15.28 | 0 | 0 |
| 19:00 | 15.19 | 15.09 | 0 | 0 |
| 20:00 | 14.99 | 14.77 | 0 | 0 |
| 21:00 | 14.54 | 14.33 | 0 | 0 |
| 22:00 | 13.77 | 13.41 | 0 | 0 |

| | | | | |
|---|---|---|---|---|
| 23:00 | 12.66 | 12.47 | 0 | 0 |
| 00:00 | 10.98 | 10.85 | 0 | 0 |
| 01:00 | 10.33 | 10.34 | 0 | 0 |
| 02:00 | 9.94 | 9.98 | 0 | 0 |
| 03:00 | 9.73 | 9.92 | 0 | 0 |
| 04:00 | 9.69 | 10 | 0 | 0 |
| 05:00 | 9.98 | 10.53 | 0 | 0 |

The terms used in the charging plan in Table 2.1. are described as follows:

1. **TimeStamp:** Represents the time of day to indicate the parameters of charging at that instant. It is created at the beginning of every full hour.

2. **Day/Hour Ahead Prediction Price:** This field represents the day- or hour-ahead predicted values of price information derived from the demand curve of the utility.

3. **Actual Cost:** It represents the actual price of power at that instant of time.

4. **Renewable:** This field represents the cost of the predicted renewable energy.

5. **Plan:** This field represents the instants at which power has been transmitted from the charging station to the Electric Vehicle based on the decision of the charging algorithm.

6. **Energy transmitted (kWh):** It is the maximum possible energy in kWh transferred from the charging station to EV before the departure time but not greater than the maximum capacity in kWh of the battery in the EV.

### 2.1.4 Proposed System Architecture

Figure. 2.2 represents the proposed system for the implementation of the smart charging scenario.

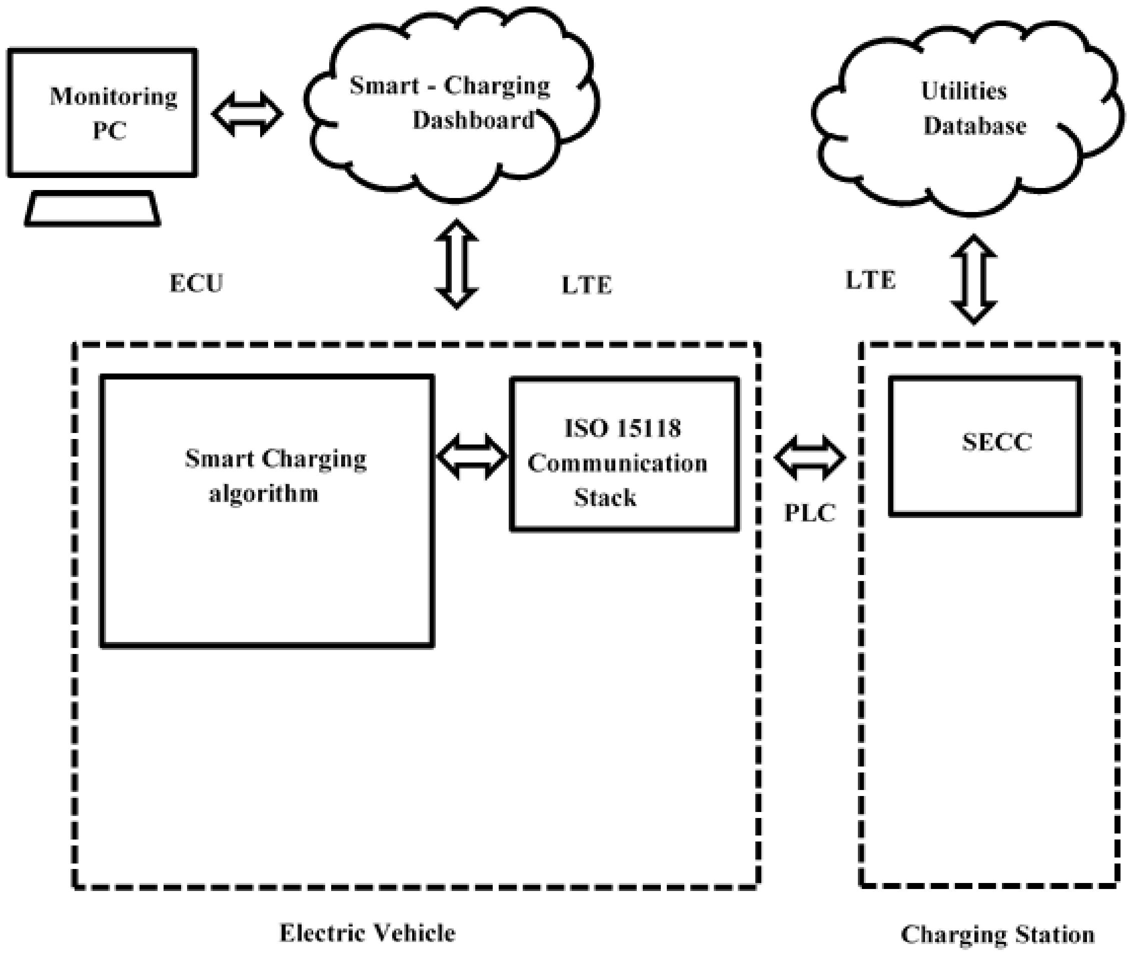


**Figure 2.2 Smart – Charging Proposed Architecture**

The description of the terms used in Figure 2.2 is given below:

1. **EVCC (Electric Vehicle Charging Controller):** ECU (Electronic Control Unit) within the Electric Vehicle, which implements the communication between the EV and the SECC.

2. **SECC (Supply Equipment Communication Controller):** Entity, which implements the communication to one or multiple EVCCs in compliance with the ISO 15118 communication protocol.

3. **ISO 15118:** ISO 15118 standardizes the communication between Electric Vehicles (EV), including Battery Electric Vehicles and Plug-In Hybrid Electric Vehicles, and the Electric Vehicle Supply Equipment (EVSE)[17].

4. **EVSE (Electric Vehicle Supply Equipment) or charging Station:** It is system in the charging setup of electric vehicles responsible for providing electric energy from the installation premises to the electric vehicles and enable communication between them[17].

5. **Smart Charging Dashboard:** It is a graphical representation of the smart charging algorithm.

6. **Utilities Database:** contains the day ahead or hour ahead prediction and the actual cost and availability of renewable energy resources. This data will be used for the creation of charging plan.

7. **PLC (Power Line Communication):** A communication protocol, which enables sending data over power cables[18]**.**

### 2.1.5 System Operation

The operation of the proposed system architecture in Figure 2.2 is described below:

1. The smart charging dashboard, hosted on either an Amazon EC2 Web service or a local server, simulating the Graphical User Interface (GUI) displayed on

the Human Machine Interface (HMI) in the infotainment system of the car, receives the inputs from the user in the form of “Price Preference” and/or “Renewable Energy Preference”,” Arrival Time”,” Departure Time”.

**2.** The parameters submitted are passed on to the ECU (Electronic Control Unit) in the EV. The ECU hosts the “Smart Charging Algorithm”. On receiving the parameters, information of “predicted cost” and “Availability of Renewable Energy resources” from the utilities database via the SECC to the EVCC, the algorithm, computes the charging plan and passes it to the SECC via the EVCC.

**3.** The SECC directs the charging station to deliver the required power, to the EV, according to the charging plan.

## 2.2 Algorithm Evaluation

To prove the viability of the smart charging algorithm and its capability to utilize the renewable energy source for EV charging, we have compared the results of its application in two main cases, namely, **1.** Power Grid is the only electricity source with renewable energy integration in scale. **2.** Home Energy Storage integrated with Power grid as the source of electricity. Each of these cases are further subdivided to four approaches, namely**, 1.** Normal EV Charging **2.** EV charging at half-rate **3.** EV charging using smart charging algorithm with perfect grid load cost information **4.** EV charging using smart charging algorithm with predicted power grid load and cost information (day- or hour-ahead prediction). The four approaches employed in each case are used to analyze: **1.** The economic benefits of smart charging, when compared to the existing normal EV charging and EV charging at half charge rate. **2.** The accuracy between actual and predicted day-ahead and hour-ahead cost of charging. This is important as charging plans can only be created based on these predictions. The algorithm must provide robust charging plan such that the most of the cost benefit can still be attained when using day-ahead and/or hour-ahead predictions.

### 2.2.1 Power-grid is the only source of electricity

In this case, we assume that the power-grid is the only source of electricity.

#### 2.2.1.1 Normal EV Charging

In this case, we charge the EV by the existing mechanism without optimization. The Figure 2.3 below evaluated a normal charging mechanism and the results have been tabulated in Table 2.2. As 6 pm is normally the time a person return home, we choose the start time at 6 pm. This will also be the start of peak hours on the Duck curve as home appliances are turned on now. If normal charging is used, EV will start charging at this very same time, which likely incur the higher utility cost due to higher price.


**Figure 2.3 Smart charging visualizer depicting normal full – rate charging of EVs**

### 2.2.1.2 Normal EV charging at half rate

In this case, we are incorporating the first level of smartness by reducing the EV charging rate by half (3kW). This has been implemented to examine the extent of decrease in the total charging cost by simply reducing the charging rate to explore the valley of the Duck curve. The graph in Figure 2.4., illustrates the case.


**Figure 2.4 Smart charging visualizer depicting normal half – rate charging of EVs**

### 2.2.1.3 EV smart - charging with actual grid load information.

In this case, we evaluate the effectiveness of application of smart charging algorithm into EV charging, with actual grid load information, which postpone the charging until a later time during the valley. Refer Figure 2.5.

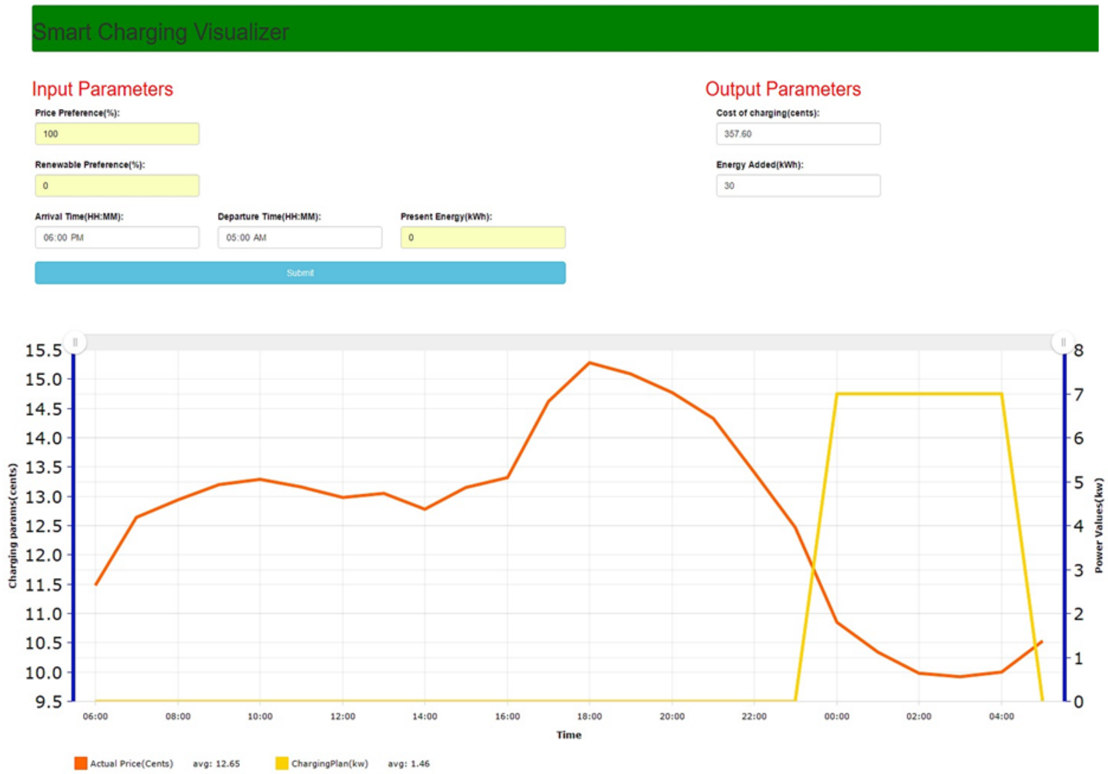


**Figure 2.5 EV charging visualizer depicting smart – charging scenario with actual grid load information**

### 2.2.1.4 EV charging using smart charging algorithm with Hour – ahead prediction.

In this case, we evaluate the application of smart – charging algorithm to the load information obtained on an hour – ahead basis.


**Figure 2.6 EV charging visualizer depicting smart – charging scenario with hour ahead predicted grid load information**

### 2.2.1.5 EV smart - charging using smart charging algorithm with Day – ahead prediction.

In this case, we evaluate the application of smart – charging algorithm to the load information obtained on a day – ahead basis. Please refer Figure 2.7


**Figure 2.7 EV smart - charging visualizer depicting smart – charging scenario with day ahead predicted grid load information**

### 2.2.2 Power-grid and Home Energy storage are the sources of energy

In this case, we consider the power – grid and the Home Energy Storage, used to store the renewable energy – solar, as the source of energy for charging.

#### 2.2.2.1 Normal EV charging.

We charge the EV by the existing mechanism devoid of optimization. The graph below gives a clear description of the mechanism. The normal charging cannot make use of the availability of the Home Energy Storage.


**Figure 2.8 EV charging visualizer depicting normal charging of EVs without smart charging and presence of solar energy**

### 2.2.2.2 Normal EV charging at half rate

In this case, we are incorporating the first level of smartness by reducing the EV charging rate. This is implemented to examine the extent of decrease in the total charging cost by reducing the charging rate. The following graph, illustrates the case.


**Figure 2.9 Smart charging visualizer depicting half – rate charging of EVs**

### 2.2.2.3 EV smart - charging with actual grid load information

In this case, we evaluate the effectiveness of application of smart charging algorithm into EV charging, with actual grid load information and ability to utilize the home energy storage. Please refer Figure 2.10


**Figure 2.10 EV smart - charging visualizer depicting smart – charging scenario with perfect grid load information and solar energy**

#### 2.2.2.4 EV charging using smart charging algorithm with Hour – ahead prediction

In this case, we evaluate the application of smart – charging algorithm to the load information obtained on an hour – ahead basis.


**Figure 2.11 EV smart - charging visualizer depicting smart – charging scenario with hour ahead predicted grid load information and solar energy**

### 2.2.2.5 EV charging using smart charging algorithm with Day – ahead prediction

In this case, we evaluate the application of smart – charging algorithm to the load information obtained on a day – ahead basis.


**Figure 2.12 EV smart - charging visualizer depicting smart – charging scenario with day - ahead predicted grid load information and solar energy.**

### 2.2.3 Summary and Comparison of Results

**Table 2.2 Comparison of results**

| Time of charge | Present energy (kWh) | Required energy (kWh) | Cost-day ahead incurred (cents) | Cost-hour ahead incurred (cents) | Cost-actual incurred (cents) | Cost – actual incurred (half - rate, non-smart) (cents) | Cost charging (full-rate, non-smart) (cents) |
|---|---|---|---|---|---|---|---|
| 18:00pm - 5:00am | 0.00 | 30.00 | 357.60 | 357.60 | 357.60 | 379.32 | 510.19 |
| 6:00 am - 17:00pm | 0.00 | 30.00 | 93.40 | 93.40 | 93.40 | 124.26 | 201.27 |

From Table 2.2, we infer the following results.

#### 2.2.3.1 Case 1: Power – Grid is the only source of energy

**1.** We have set a charging time from 18:00pm to 5:00am, because the highest and the lowest cost of charging are present within this interval. This represents an ideal time – span to illustrate the benefits of smart charging over regular charging. Further, it is the time when most the EV driving population charge their vehicles.

**2.** The cost of charging at full rate without smart charging, 510.19 cents are greater by 152.59 cents compared to the cost of charging with smart charging algorithm. Further, the cost of charging at half-rate (3kW) without smart-charging is higher by 21.72 cents compared to charging at full rate with smart charging (6.6kW ~ 7kW) [19], clearly demonstrating economic benefits of smart – charging algorithm.

**3.** The cost of charging for day-ahead, hour-ahead and actual tariff for charging is 357.60 cents. This proves that the predictions are as good as the actual tariff and can be used to make decisions pertaining to charging in advance, by a day or hour.

#### 2.2.3.2 Case 2: Home solar energy source with power grid is the source of energy

**1.** We have set a charging time from 6:00am to 17:00pm, as majority of the solar energy is captured within this time – span. Moreover, it represents the ideal time-span to illustrate the use of smart-charging algorithm to maximize the integration of renewable energy resource for EV charging.

2. Further, we observe that by charging at half – rate (3kW), instead of full-rate we can reduce the charging costs by 201.27 – 124.26 = 77.01 cents. However, the cost of charging at half rate is still higher by 124.26 – 93.40 = 30.86 cents compared to cost incurred due to smart – charging.

3. The cost of charging at full-rate (7kW) without smart charging is higher by 201.47 – 93.40 = 108.07 cents.

### 2.2.4 Conclusion

From the above calculations, we can conclude that:

1. The smart charging algorithm enable EVs to charge intelligently to accommodate the maximum availability of solar energy.

2. The smart-charging algorithm is the better alternative compared to the 1. Charging by half-rate 2. Charging by full-rate as it incurs the least cost of charging.

3. The day-ahead and the hour-ahead predictions of demand and hence the tariff can be used to make charging decisions in advance, by a day or hour. Consequently, EV load information to the utilities in advance, which allows them to prepare for any unseen issues pertaining to overloading.

4. The predicted load by the utility can be reliably used to make charging decisions because the cost incurred due to predictions are approximately equal to the cost due to the actual load.

# Chapter 3. A Machine Learning approach to Smart Charging of EVs

In this chapter, we present the second solution to further improve the smart charging performance by using machine-learning paradigms namely, logistic regression and fuzzy logic. One of the major goals of this new solution is to produce charging schedule that: 1. Better harness the renewable energy; 2. Mitigate the potential peak demand caused by simultaneous EV charging because of smart charging (Approach 1); and, 3. Improve the battery life by optimizing the charging cycles. Thus, we will explore the individual EV's usage/charging pattern to provide the flexibility in its charging cycle, such as time and frequency. This approach was considered, to explore the following cases: **1.** Profiling and classification of users based on customer charging habits to produce personalized charging plans. Contributing to improvements in the durability of the battery **2.** Introduce autonomy into charging to prevent human interaction, which is the weakest element in the link.

## 3.1 Assumption

For the sake of practicality and convenience, we have made the following assumptions to build the machine learning model. They can be classified into:

### 3.1.1 System (Vehicle) Assumptions

1. EV will become the main stream passenger automobile. We assume there will be no difference in the EV driving characteristics, compared to the present day Internal Combustion Engine(ICE) vehicles. This assumption is essential, because the success of EVs depends on their seamlessness into mainstream adoption.
2. The total battery capacity is 40kWh.
3. As the discharge curve of the Li – ion based battery is linear for most of the duration; we generalize it to a linear function of time.
4. Regenerative braking - a modern day feature in all electric vehicles, responsible for converting the kinetic energy of a moving object or vehicle into a form of energy, here electricity, to be stored for immediate or future use, has been ignored as its contribution to the cumulative energy at any given instant of time does not significantly contribute to the drive.

### 3.1.2 User Profile Assumptions

EV charging habits of the general population can be inferred from their driving habits. We classify this correlation into three categories:

#### 3.1.2.1 Category 1

Higher frequency of usage of the EV (Frequency of usage is defined as the number of round trips between two locations) but less battery consumption per trip. This would result in a higher number of plug-ins from the charging station, but lesser consumption of electric energy. Homemakers and the elderly are prime representatives of this class.

#### 3.1.2.2 Category 2

Through this category, we target the second most automobile driving population in i.e. the office – commuters and students. For these class of people the usage of the EV is to commute between residence to workplace, with frequency of around trips being minimal and battery usage being minimal (about 30%). Here the number of plug-ins from charging station can be low and the energy derived from the grid is calculated to be low owing to lower usage.

#### 3.1.2.3 Category 3

This category represents the heavy users, for example sale person, mail – delivery and public transportation. High battery consumption and high frequency of usage are the characteristics of this case. The main characteristics of this class of users are low plug-in number and higher electric energy consumption.

In this thesis, we limit our attention to these 3 categories: Homemaker, Daily commuter and Delivery person, that represent the three-major trends in driving characteristics of most the driving population. Thus, they represent the three classes for the smart charging classifier.

## 3.2 Smart - Charging System Visualization

To visualize operation of the smart charging case, we propose a systems engineering approach as shown in Figure 3.1

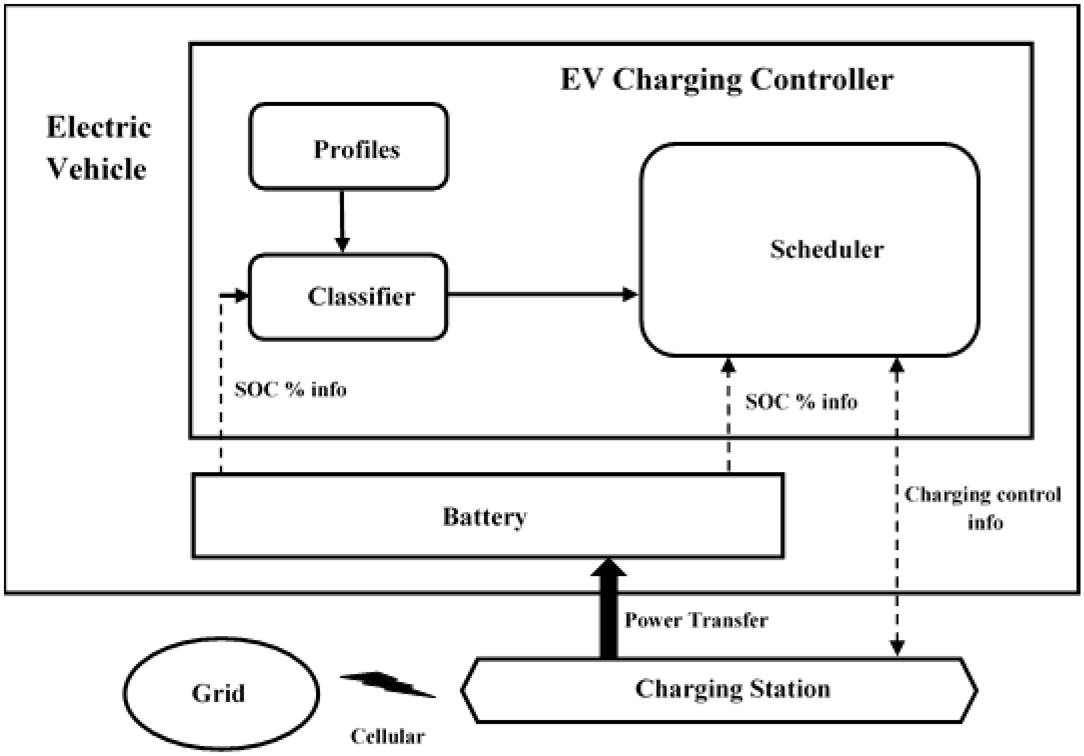


**Figure 3.1** **Smart charging system**

Figure 3.1. represents the smart – charging system visualization implemented using the machine learning approach. The components that constitute the system are described in the following section.

### 3.2.1 System description

1. **EV Charging Controller(EVCC):** ECU (Electronic Control Unit) within the Electric Vehicle, that implements the communication between the EV and the SECC. It contains a memory module that stores the charging profiles and the software implementations of the classifier algorithm and the charge scheduler. It is also responsible for monitoring the battery status during charging process and sharing the battery state of charge info to the profiler and the scheduler.

2. **Profiler:** Currently it is a database in the EVCC that contains the labelled charging profiles of the three most prominent charging patterns. The stored profiles under consideration are 1. Home – maker 2. Regular – commuter 3. Delivery person. In future work, we expect to develop an autonomous profiler which can create new profiles by monitoring the usage/charging patterns.

3. **Classifier:** It is the implementation of the machine learning algorithms like logistic regression or fuzzy logic used to classify the charging data based on the profiles in the profiler.

4. **Scheduler:** The scheduler is responsible for preparing a charging plan based on the class chosen by the classifier.

5. **Battery:** The battery in the EV is used mainly for propulsion. It is arranged in the form of cells, modules and packs with cells representing the fundamental form a battery can take. Several cells are arranged in series or in parallel to constitute a module and similarly a group of modules are arranged in series or in parallel to constitute a battery pack[20].

6. **EVSE (Electric Vehicle Supply Equipment) or charging Station:** It is system in the charging setup of electric vehicles responsible for providing electric energy for the charging of electric vehicles.

7. **Electric Grid:** An electric grid is an interconnected network of generating stations, transmission lines and distribution transformers used to transmit power from the generating end to the end users[21].

### 3.2.2 System function

**1.** The charging data consisting of plug in time, plug out time, departure time, initial state of charge is logged by the EVCC. The machine learning algorithm consisting of the profiler and the classifier which learns this charging pattern over time and classifies the user into one of the different profiles of users, currently limited to: 1. Home – maker (Representing medium usage) 2. Regular – commuter (Representing light usage) 3. Delivery person (Representing heavy - usage).

**2.** This profile info along with the next probable departure time is sent to the scheduler. The scheduler prepares a charging plan per this information and sends it to the charging station via the Power Line Communication (PLC) in accordance with the ISO 15118 protocol.

**3.** The charging station receives the charging plan from the EVCC and transfers power to the EV accordingly.

## 3.3 Implementation

For feature creation, a mathematical model of the charging behavior for each profile was created. A preprocessing algorithm is used to derive the high-level features for easier classification between the output classes. This feature data is then given as an input to the classifier that outputs the corresponding class.

Figure 3.2. Gives a schematic of our approach to the profiler and classifier setup.

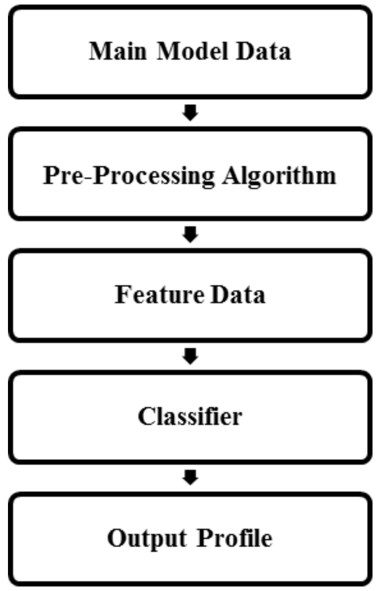


**Figure 3.2** **Smart Charging Classifier Flow-chart**

The description of each of the elements in the flowchart are given below:

### 3.3.1 Main Model Data

We have chosen three different patterns of charging data, representative of each profile on a given day. These driving data primarily represent the weekday driving habits. The waveforms in the ensuing subsections are used to provide a pictorial representation of the data.

#### 3.3.1.1 Charging Profile: Home-maker

**Charging Pattern 1.1 Typical charging profile #1 for home-maker starting S.O.C. = 100%**

We have assumed the typical charging profile #1 for home – maker:

7-9am → Drop kids at school and/or Grocery shopping

10-11am → home errand

2-3pm → pickup kids from school

5-7pm → other activities

Based on the above schedule we have come up with 3 possible main cases of charging characteristics and 3 subcases. The subcases represent the 3-different starting S.O.C. (State of Charge).

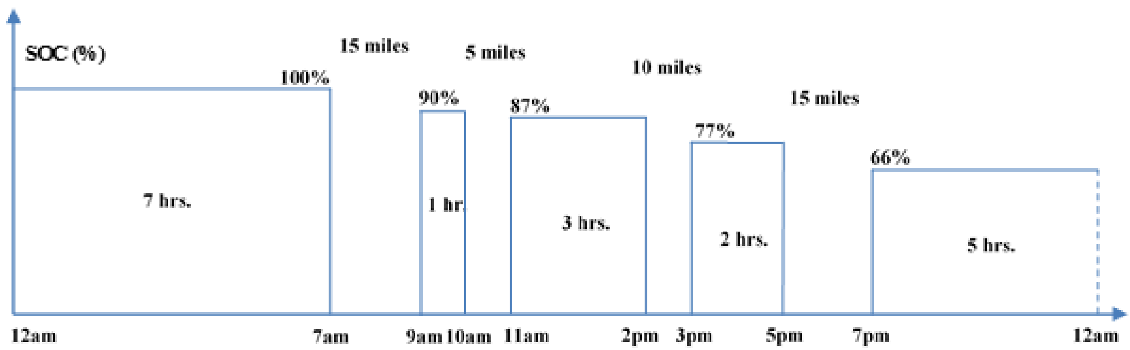


**Figure 3.3 Graphical representation of typical charging profile #1 for home – maker at S.O.C = 100% for Charging pattern 1.1**

**Charging Pattern 1.2 Typical charging profile #1 for home-maker starting S.O.C. = 75%**

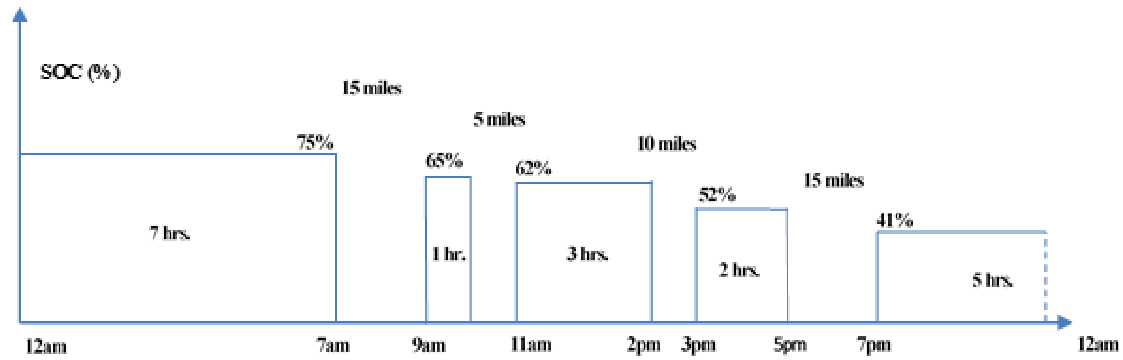


**Figure 3.4 Graphical representation of typical charging profile #1 for home – maker at S.O.C = 75% for Charging pattern 1.2.**

**Charging Pattern 1.3 Typical charging profile #1 for home-maker starting S.O.C. = 50%**

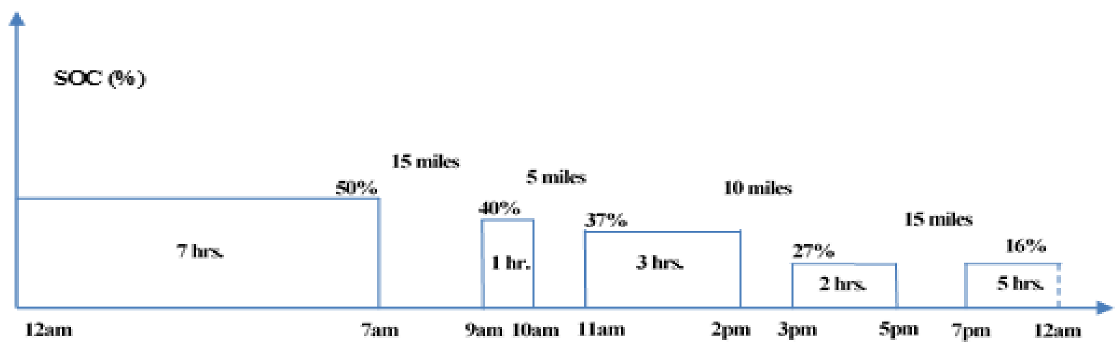


**Figure 3.5 Graphical representation of typical charging profile #1 for home – maker at S.O.C = 50% for Charging pattern 1.3**

**Charging Pattern 2.1 Typical charging profile #2 for home-maker starting S.O.C. = 100%**

The following section represents typical charging profile #2 for the home – maker class:

5-7am → Gym and exercise

8-10am → Drop kids at school

2-4pm → pickup kids from school

5-7pm → other activities

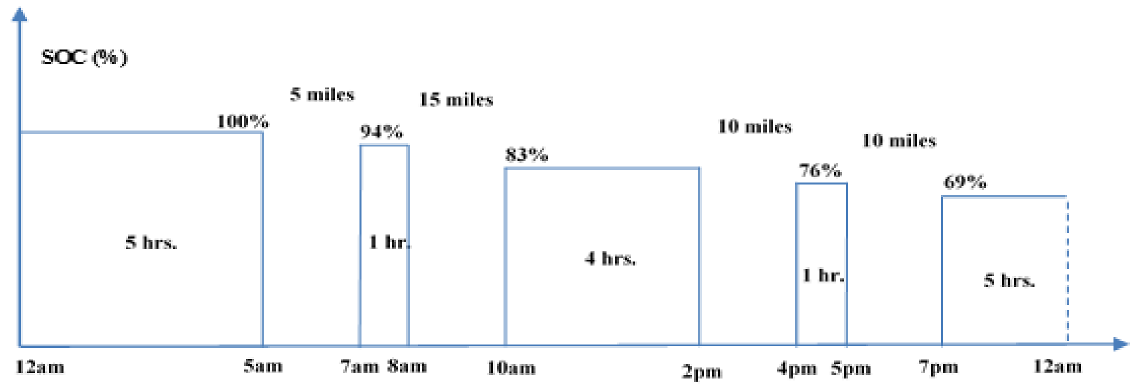


**Figure 3.6 Graphical representation of typical charging profile #2 for home – maker at S.O.C = 100% for Charging pattern 2.1**

**Charging Pattern 2.2 Typical charging profile #2 for home-maker starting S.O.C. = 75%**

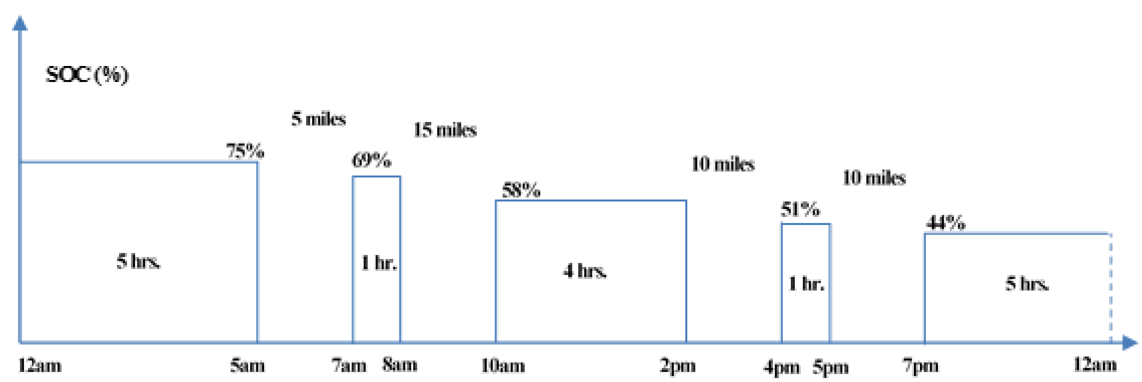


**Figure 3.7 Graphical representation of typical charging profile for home – maker at S.O.C = 75% for Charging pattern 2.2.**

**Charging pattern 2.3 Typical charging profile #2 for home-maker starting S.O.C. = 50%**

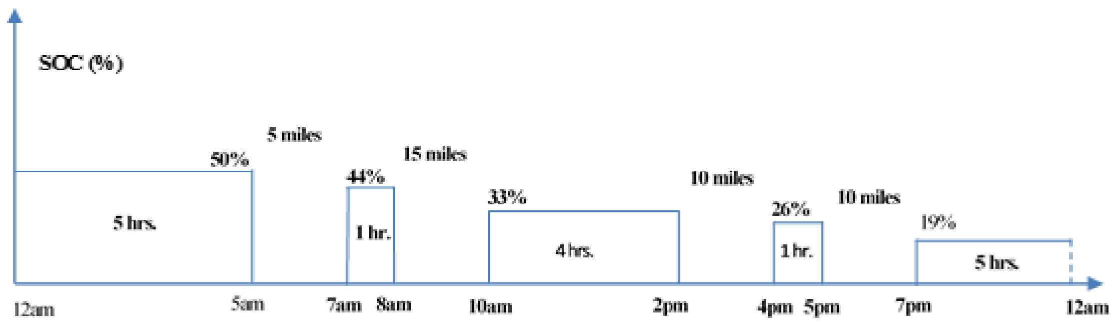


**Figure 3.8 Graphical representation of typical charging profile for home – maker at S.O.C = 50% for Charging pattern 2.3.**

**Charging Pattern 3.1 Typical charging profile #3 for home-maker starting S.O.C. = 100%**

We have assumed the following typical charging profile #3 for a home – maker.

10am-1pm → yoga/arts/martial arts class

5-7pm → other activities

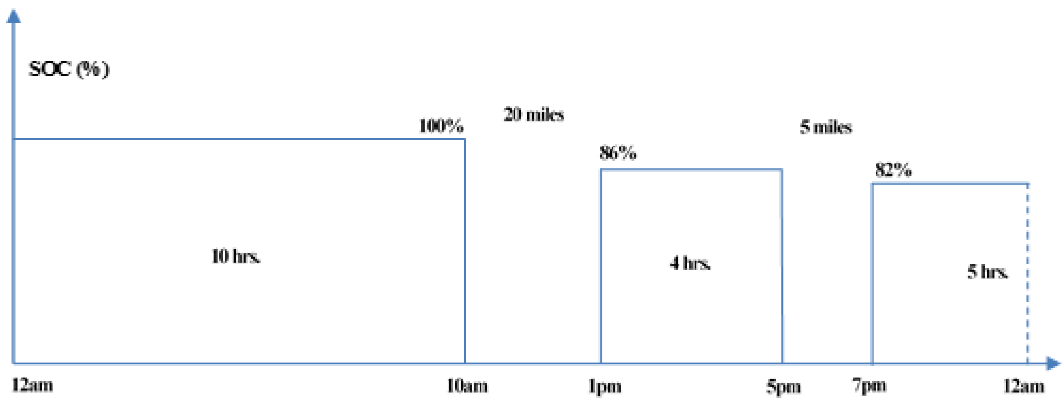


**Figure 3.9 Graphical representation of typical charging profile #3 for home – maker at S.O.C = 100% for Charging pattern 3.1.**

**Charging pattern 3.2 Typical charging profile #3 for home-maker at starting S.O.C. = 75%**

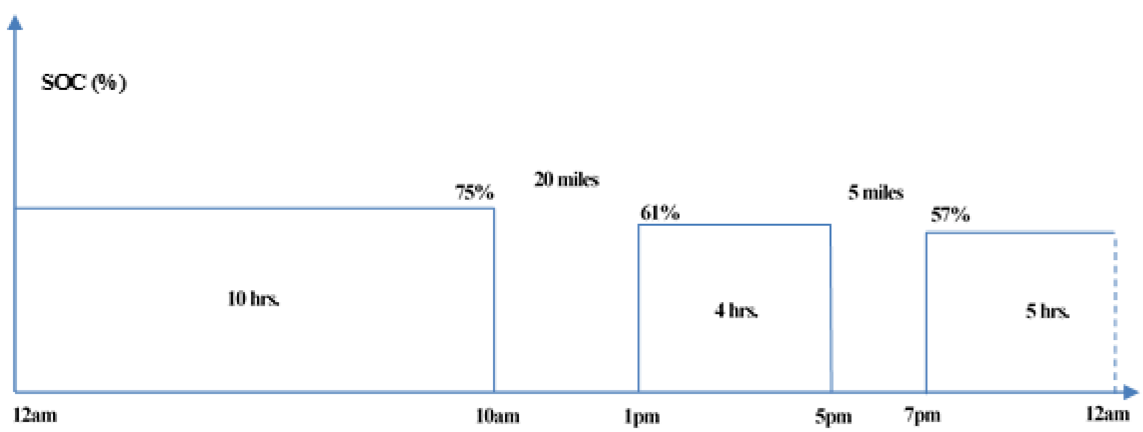


**Figure 3.10 Graphical representation of typical charging profile #3 for home – maker at S.O.C = 75% for Charging pattern 3.2**

**Charging pattern 3.3 Typical charging profile #3 for home-maker starting S.O.C. = 50%**

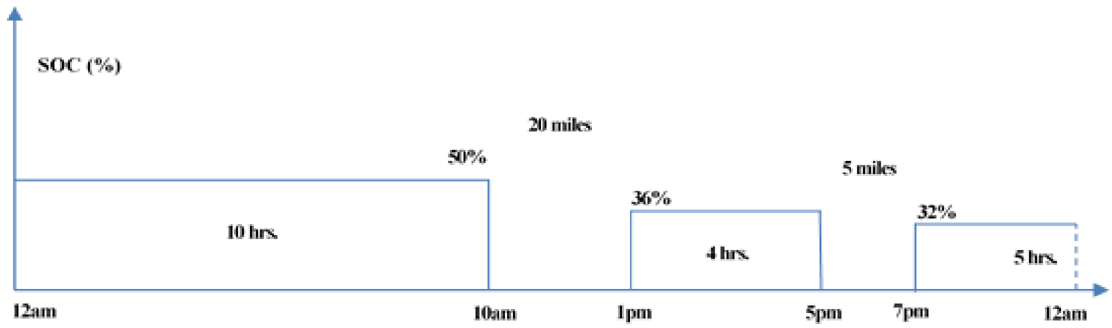


**Figure 3.11 Graphical representation of typical charging profile #3 for home – maker at S.O.C = 50% for Charging pattern 3.3.**

### 3.3.1.2 Charging Profile: Daily Commuter

Assumption: Daily commuter do not charge during afternoon (or at work place). Further, for each charging pattern we have considered 3 different starting SOCs.

Based on this assumption we propose the following schedule for the daily commuter class.

9am-6pm → office usage (20-mile drive back and forth at 0.25kwh / mile)

**Charging pattern 4.1 Typical charging profile #1 for Daily Commuter at starting S.O.C. = 100%**

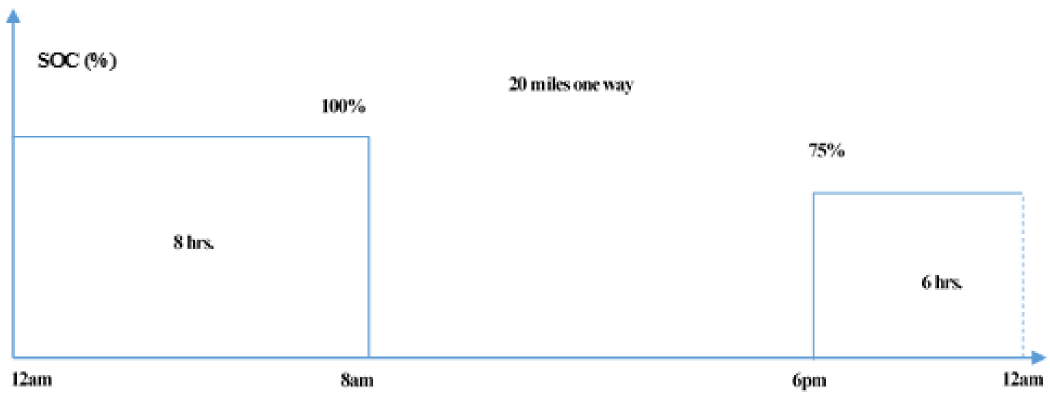


**Figure 3.12 Graphical representation of typical charging profile for daily - commuter at S.O.C = 100% for Charging pattern 4.1**

**Charging pattern 4.2 Typical charging profile for Daily Commuter at starting S.O.C. = 75%**

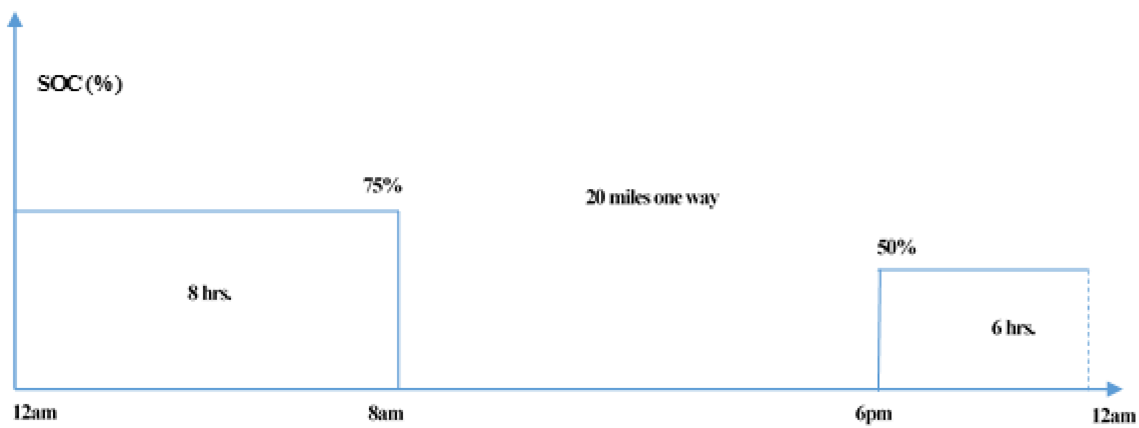


**Figure 3.13 Graphical representation of typical charging profile #1 for daily commuter at S.O.C = 75% for Charging pattern 4.2**

**Charging pattern 4.3 Typical charging profile #1 for Daily Commuter at starting S.O.C. = 50%**

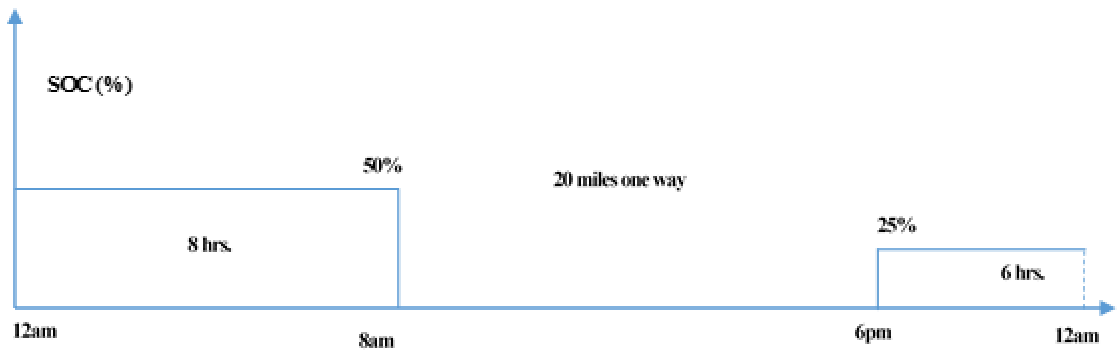


**Figure 3.14 Graphical representation of typical charging profile #1 for daily commuter at S.O.C = 50% for Charging pattern 4.3**

**Charging pattern 5.1 Typical charging profile #2 for Daily Commuter at starting S.O.C. = 100%**

We propose the following schedule for the daily commuter class:

9am-6pm → office usage (20-mile drive back and forth at 0.27kwh / mile)

7pm-8pm → Dinner (10-mile drive back and forth at 0.27kwh / mile)

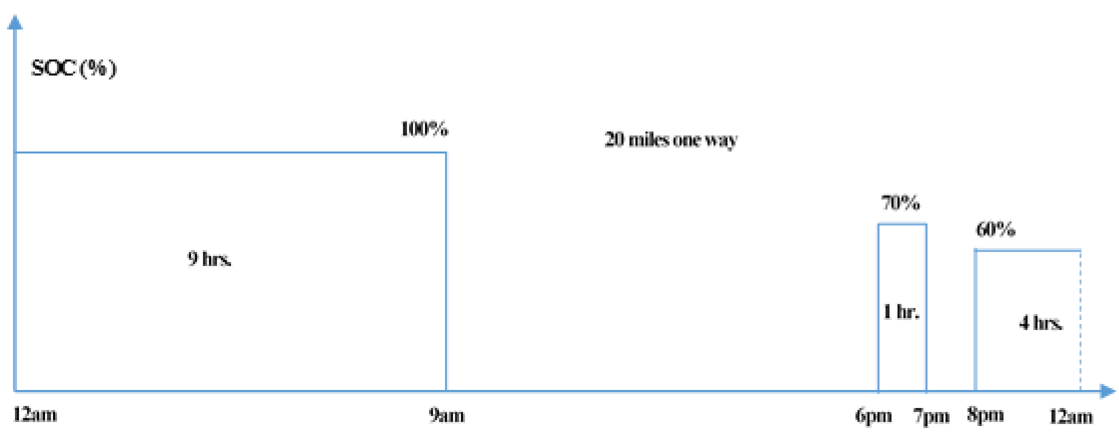


**Figure 3.15 Graphical representation of typical charging profile #2 for daily commuter at S.O.C = 100% for Charging pattern 5.1.**

**Charging pattern 5.2 Typical charging profile #2 for Daily Commuter at starting S.O.C. = 75%**

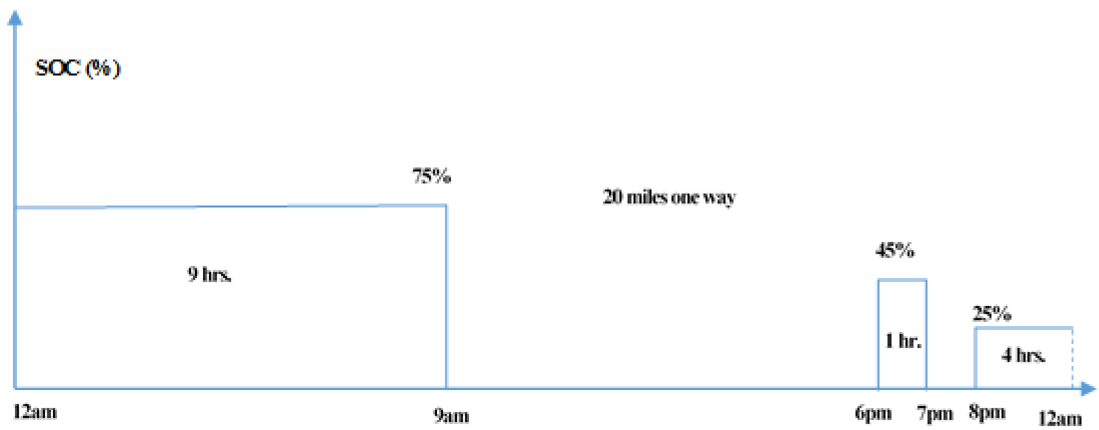


**Figure 3.16 Graphical representation of typical charging profile #2 for daily commuter at S.O.C = 75% for Charging pattern 5.2.**

**Charging pattern 5.3 Typical charging profile #2 for Daily Commuter starting S.O.C. =50%**

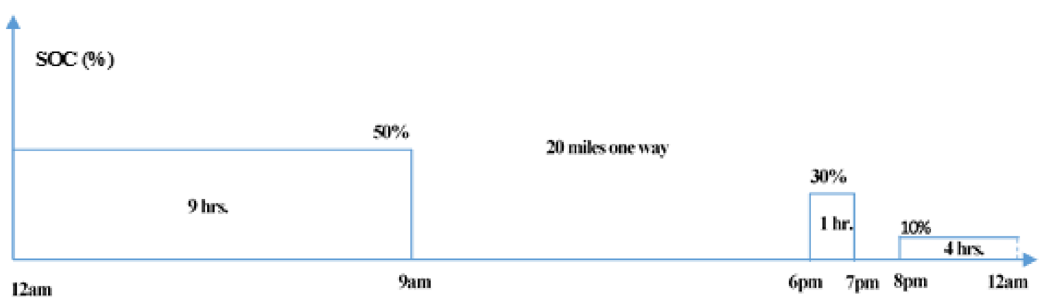


**Figure 3.17 Graphical representation of typical charging profile #2 for daily commuter at S.O.C = 50% for Charging pattern 5.3**

**Charging pattern 6.1 Typical charging profile #3 for Daily Commuter at starting S.O.C. = 100%**

We have assumed the following pattern for charging.

8am-5pm → office usage (20-mile drive back and forth at 0.27kwh / mile)

6am-7am → Gym/Exercise (10-mile drive back and forth at 0.27kwh / mile)

7pm-8pm → Dinner (10-mile drive back and forth at 0.27kwh / mile)

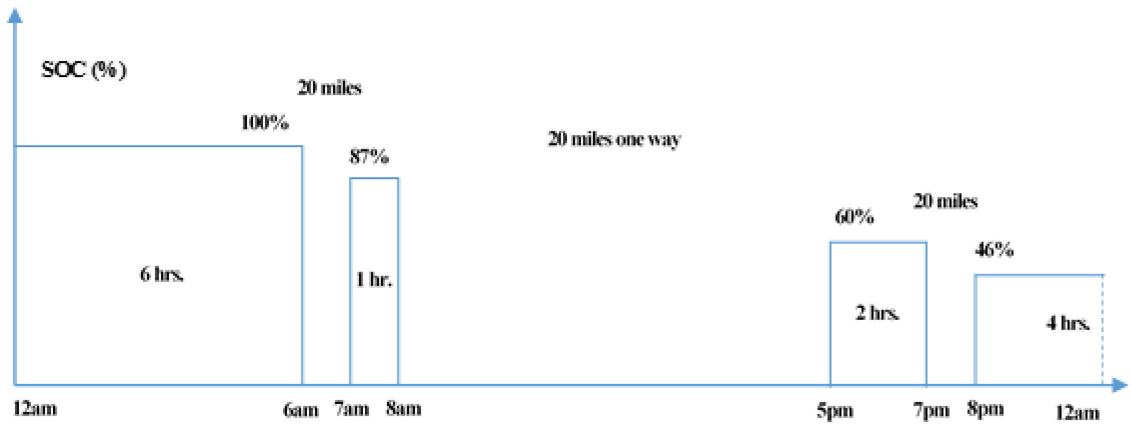


**Figure 3.18 Graphical representation of typical charging profile #3 for daily commuter at S.O.C = 100% for Charging pattern 6.1**

**Charging pattern 6.2 Typical charging profile #3 for Daily Commuter at starting S.O.C. = 70%**

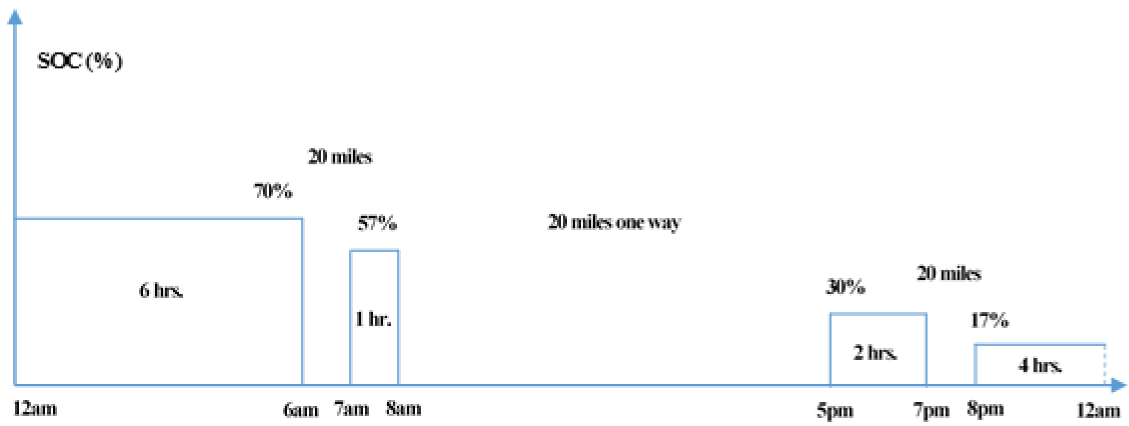


**Figure 3.19 Graphical representation of typical charging profile #3 for daily commuter at S.O.C = 70% for Charging pattern 6.2**

**Charging pattern 6.3 Typical charging profile #3 for Daily Commuter starting S.O.C. = 50%**

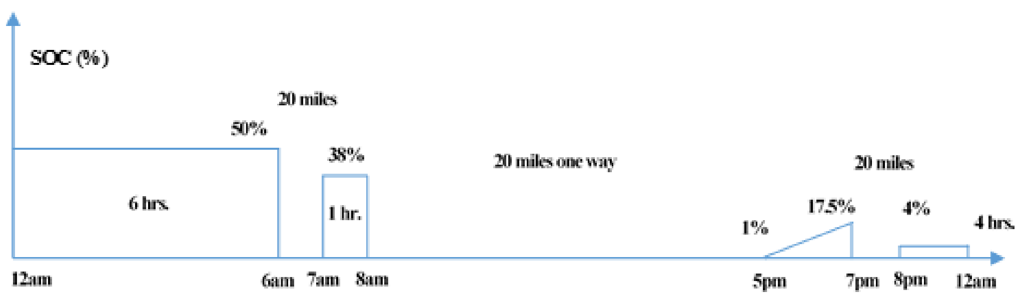


**Figure 3.20 Graphical representation of typical charging profile #3 for daily commuter at S.O.C = 50% for Charging pattern 6.3**

Note: Increasing slop in graph denotes battery charging. Constant slop denotes no change in battery charging level. Between 5pm and 7pm, the SOC increases from 1% to 35%. From the duck curve in Figure 1.1, we know that the prices will be very high during this period. If the car decides to charge at 3.5kW (0.5 * 7kW), after two hours we end up with 17.5% which is just enough to complete the "Dinner" trip.

#### 3.3.1.3 Charging Profile: Delivery Person

**Charging pattern 7.1 Typical charging profile #1 for Delivery Person starting S.O.C. = 100%**

We propose the following schedule for the Delivery person. For each different charging pattern, we have proposed three different sub – patterns, each representative of a different starting SOC.

9am-6pm → Delivery person usage (80 miles for USPS delivery at 0.27kwh / mile).

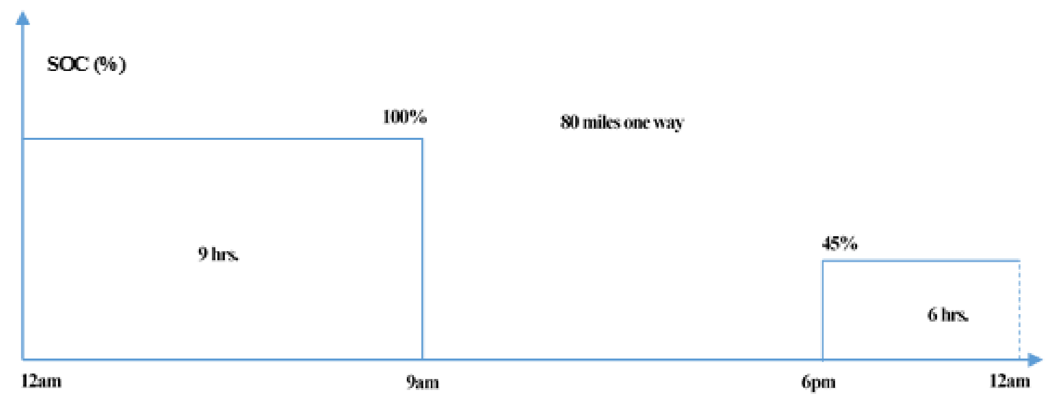


**Figure 3.21 Graphical representation of typical charging profile for delivery person at S.O.C = 100% for Charging pattern 7.1**

**Charging pattern 7.2 Typical charging profile #1 for Delivery Person starting S.O.C. = 75%.**

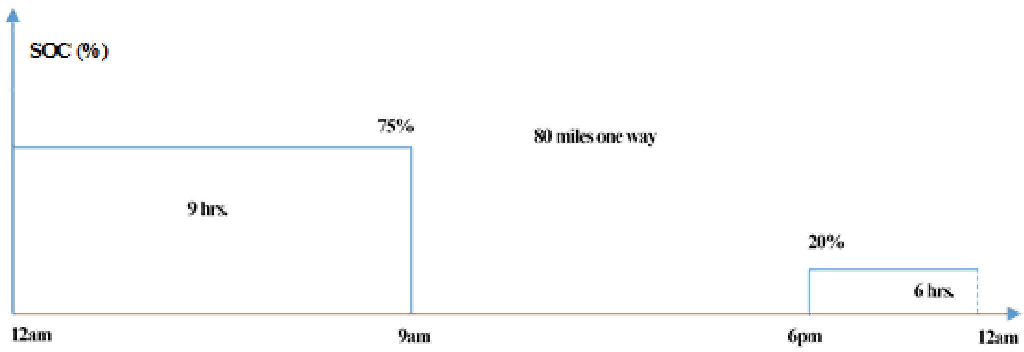


**Figure 3.22 Graphical representation of typical charging profile #1 for delivery person at S.O.C = 75% for Charging pattern 7.2.**

**Charging pattern 7.3 Typical charging profile #1 for Delivery Person starting S.O.C. = 50%**

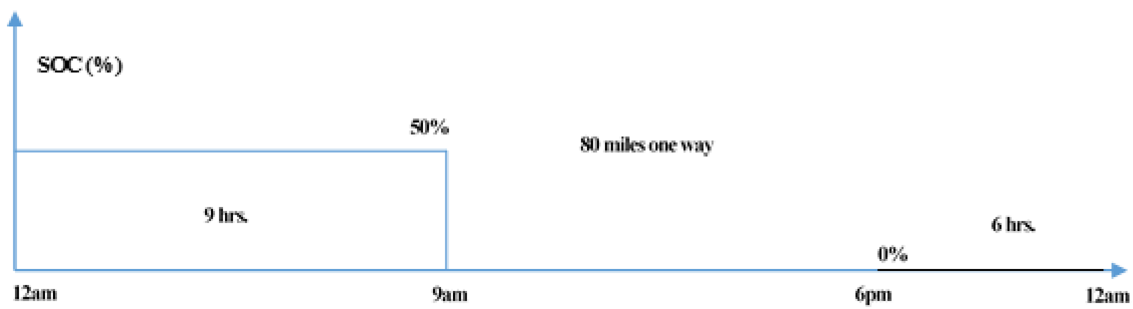


**Figure 3.23 Graphical representation of typical charging profile #1 for delivery person at S.O.C = 50% for Charging pattern 7.3.**

**Charging pattern 8.1 Typical charging profile #2 for Delivery Person starting S.O.C. = 100%**

We have assumed the following schedule for the Delivery person.

9am-12pm → Delivery (50 miles at 0.27kwh / mile)

1pm-6pm → Delivery (50-mile drive back and forth at 0.27kwh / mile)

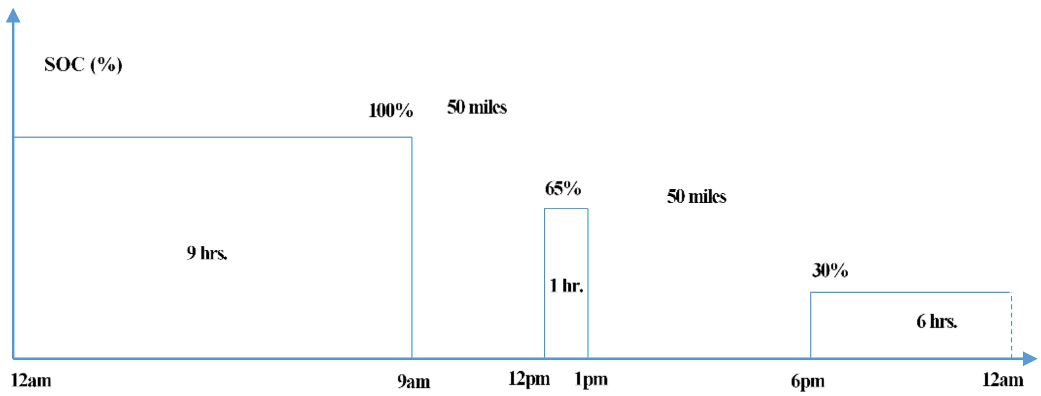


**Figure 3.24 Graphical representation of typical charging profile #2 for delivery person at S.O.C = 100% for Charging pattern 8.1**

**Charging pattern 8.2 Typical charging profile for Delivery Person starting S.O.C. = 75%**

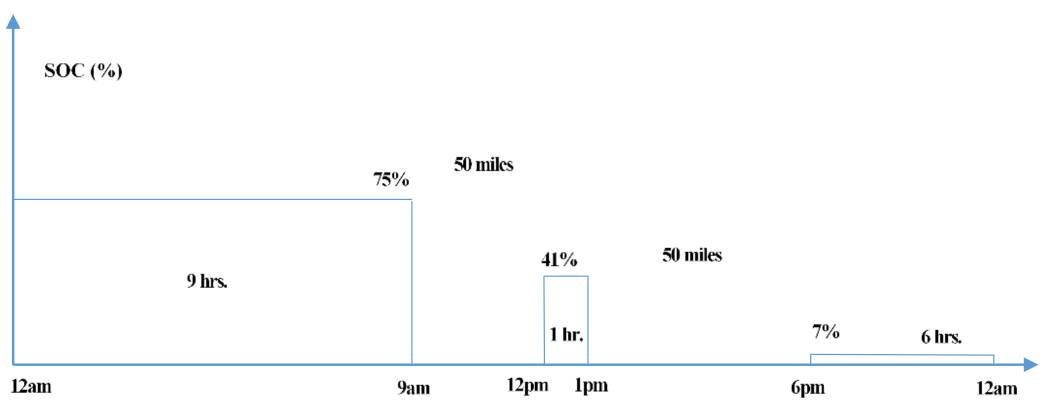


**Figure 3.25 Graphical representation of typical charging profile #2 for delivery person at S.O.C = 75% for Charging pattern 8.2**

**Charging pattern 8.3 Typical charging profile #2 for Delivery Person starting S.O.C. = 50%**

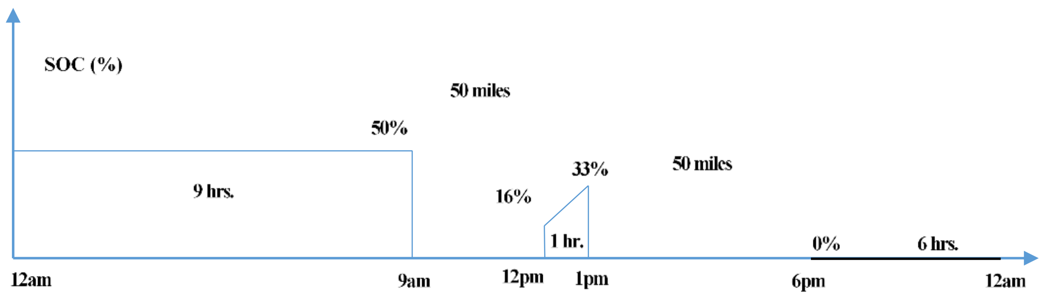


**Figure 3.26 Graphical representation of typical charging profile #2 for delivery person at S.O.C = 50% for Charging pattern 8.3**

**Charging pattern 9.1 Typical charging profile #3 for Delivery Person starting S.O.C. = 100%**

We propose the following schedule for the delivery person class.

8am- 12pm → Delivery usage (60-mile drive at 0.27kwh / mile)

1pm - 6pm→ Delivery usage (40-mile drive at 0.27kwh / mile)

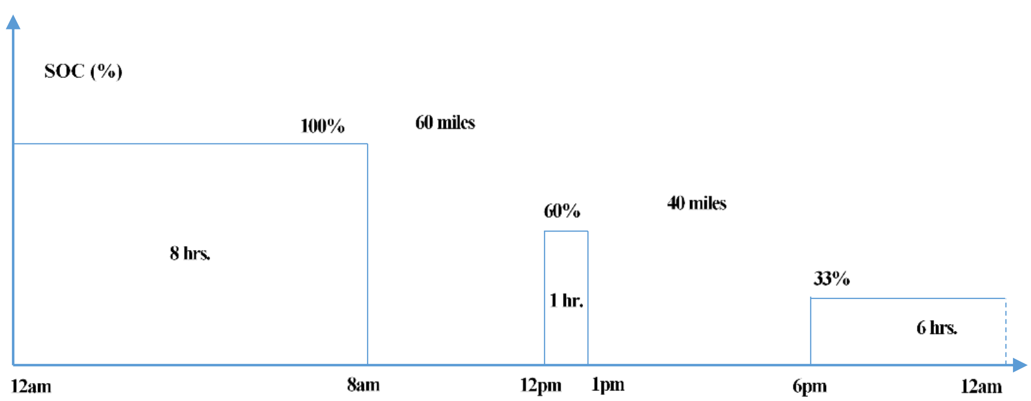


**Figure 3.27 Graphical representation of typical charging profile #3 for delivery person at S.O.C = 100% for Charging pattern 9.1**

**Charging pattern 9.2 Typical charging profile #3 for Delivery Person starting S.O.C. = 75%**

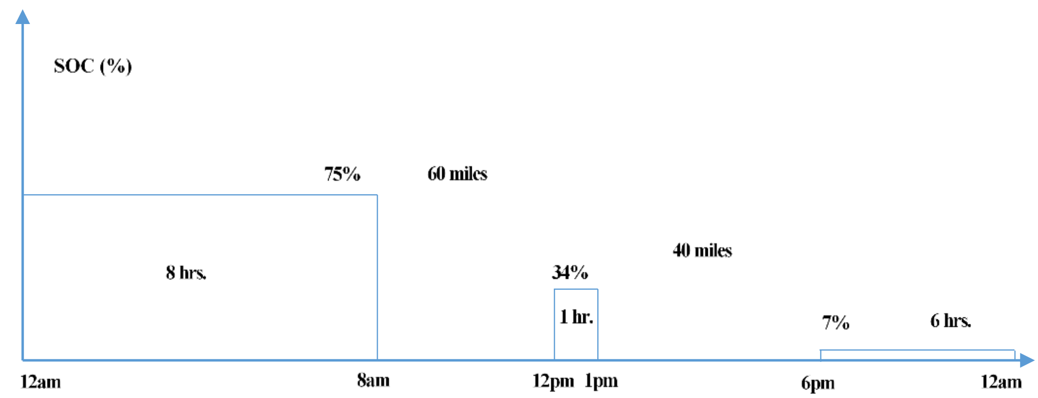


**Figure 3.28 Graphical representation of typical charging profile #3 for delivery person at S.O.C = 75% for Charging pattern 9.2**

**Charging pattern 9.3 Typical charging profile #3 for Delivery Person starting S.O.C. = 50%**

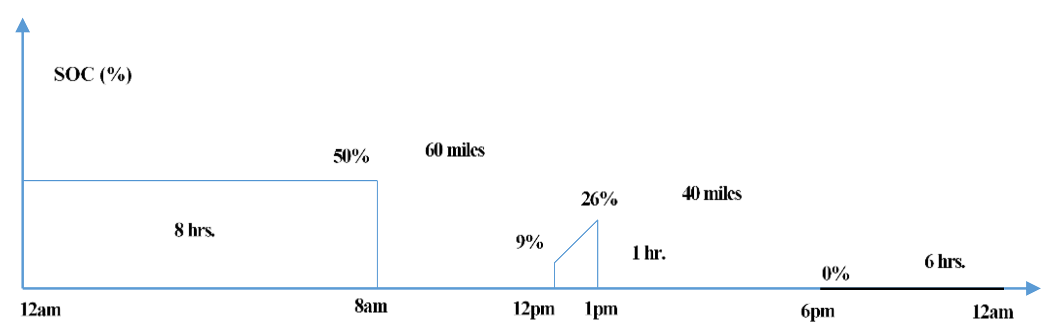


**Figure 3.29 Graphical representation of typical charging profile for delivery person at S.O.C = 50% for Charging pattern 9.3**

#### 3.3.1.4 Main model data description

This section contains a description of all the main features extracted from the charging patterns from subsections 3.3.1.1 to 3.3.1.3:

1. **Time Stamp:** It represents the hourly time stamps at which data has been sampled.

2. **Number of Plug ins**: Denotes the number of times each user has plugged the charging cable from the charging station to the electric vehicle.

3. **SOC (State of charge):** Represents the available battery charge in terms of percentage. The battery capacity chosen for our model is 40kWh.

4. **Difference in SOC:** Primarily used to signify the battery consumed on an hourly basis. This data is inferred indirectly from the SOC at the beginning of vehicle journey and the time at which it is plugged back in to charge.

5. **Plug – in / plug - out:** Represents the state of plugin of the charging cable into the electric vehicle. State 1 signifies “plugged-in” state and 0 signifies “plugged-out” state.

6. **Duration of Plug-out:** Represents the time duration of total plug-out (Disconnection between the charging station and the EV) time in minutes.

7. **Class:** Represents the numeric label of the class. Class 1. Homemaker, Class 2. Daily commuter, Class 3. Delivery person.

8. **Number of Instances of Battery Usage:** Represents the number of times the EV is in a state of relative motion. Consequently, this term represents the number of times the battery is used.

### 3.3.2 Generation of Derived Features for the Classifier

As it was not possible to compare the 24 data points of an entire day of a profile with the 24 data points of another profile for classification, we needed a mechanism to consolidate the data corresponding to 24 time – instants of a day into a single data point. This led to the conceptualization of a preprocessing algorithm. The preprocessing algorithm is used to aggregate the data of an entire day (24 hrs.). This data, used as feature for classification, contributes to better distinguishability between profiles thus helping in better decision-making.

Further, on close observation it can be observed that some features in the main model can be derived from the other features. For example: "Duration of Plug-out" can be inferred from the "Plug-in instance" data, whenever the EV is unplugged from the charging station, indicated by 0 we combine the number of repetitions of these 0s and multiply the same with hourly data to find the total plug-out time.

The following data represent the derived high-level features used as inputs to the Classifier.

1. **Number of Instances of Battery Usage:** Based on our literature survey, we found out that the people in the service industry like public transport and mail - delivery had the highest stop and move instances than the rest of the population. Similarly, we infer from section 3.3.1.1. that typical homemakers have more

stop-move instances than daily-commuters as they have a higher frequency of usage of personal vehicles.

2. **Plug-In Number:** We understand from section 3.3.1.1. that Home-makers have a higher "Number of charger plugins" than other profiles as they return home more often than the other two profiles.

3. **Battery Consumption:** We infer from the main model that the Battery consumption is higher for the "Delivery person" profile than the other two profiles as they logged a higher number of driving miles and have higher stop and move instances than the other two profiles.

4. **Duration of Plug-In:** The duration of plug-in is highest for the home-maker as the EVs tend to be parked for a longer duration than the other two profiles.

From the above inferences, we can conclude the said features to be the feature inputs into the classifier algorithm.

### 3.3.3 Choice of Classifier Algorithms

The main aim of our project is to prototype a charging system, and bring it to fruition as soon as possible. To do so, we needed algorithms that could help us reduce our development time and simultaneously produce tangible results to draw more informed conclusions. Further, the following details of our problem domain helped us narrow down our search for the appropriate classifier algorithm.

#### 3.3.3.1 Limitation in the number of data points for the features

The number of data points that could be used, considering one data point a day for the nine patterns resulted in a decrease in feature data size. Hence, we needed an algorithm that can work on this limited amount of data.

#### 3.3.3.2 Possibility of high variations in data pattern from one day to another

A person may exhibit a charging pattern of a homemaker for two days and Daily commuter on the third. This created a requirement for us to use an algorithm that can accommodate drastic change in charging behavior and yet produce a charging plan to keep the EV charged for the following day. We also give the user the option to override the charging plan in case of drastic change from daily routine. In the future, we expect to build a combination of big data, deep learning cross different data sets including, e.g., text calendar/txt/social media, and context aware computing technologies that can be used to leverage both structured and unstructured data generated by EV users to create richer and more accurate profiles to personalize driving/charging or other activities.

#### 3.3.3.3 Need for interpretability and Simplicity

Even though charging in the EV is autonomous without the need for human intervention, it is important to display the results of this charging behavior to the owner or the technician for monitoring or debugging purposes. Hence, there is a need to represent the membership functions as linguistic variables.

This led us to choose Fuzzy logic as our algorithm of choice as we could define its membership functions using linguistic variables thereby making it comprehensive. The membership functions also provide a range to accommodate noise as input variables.

Further, the GUI (Graphic User Interface) development environment on Matlab makes it convenient to reduce the development time needed to prototype the charging system. Further, we include logistic regression in the implementation to compare the performance of Fuzzy Logic with a conventional learning algorithm.

### 3.3.4 Implementation of Classification Algorithms

#### 3.3.4.1 Logistic Regression Approach "One versus One"

The charging profile learnt by the vehicle must be classified into three classes. This creates an issue with logistic regression as it is a binary classifier. Consequently, "One versus one" approach was chosen to address this multi-class classification problem. According to this approach, we build three classifiers that compare only two classes each, then the test data is fed to all the three classifiers and a "Voting-Scheme" is implemented, where majority of votes received for the correct predictions by the three classifiers determines the final output class.

Example: if there are three output classes 1 = Homemaker, 2 = Daily Commuter and 3 = Delivery Person, we build three classifiers, namely, Classifier2_1_1 (Classifier that separates class 2 and 1 with class 2 being the positive class), similarly Classifier1_3_1 and Classifier3_2_1. If given test data point is assigned to class 1 by two classifiers, then irrespective of the output from the third classifier the test data point is considered to belong to class 1.

##### 3.3.4.1.1 Classifier2_1_1

(**To be read as: Classifier that separates class 2 and 1 with class 2 being the positive class**)

The following subsections represent the specifications of the logistic regression classifier.

#### 3.3.4.1.1.1 Inputs

**1. Features**

**a.** Number of Instances of Battery Usage

**b.** Plug-In Frequency

**c.** Battery Consumption

**d.** Duration of Plug-In

**2. Initial Theta Values**

$\Theta_0 = 1$ $\Theta_1 = 1$ $\Theta_2 = 1$ $\Theta_3 = 1$ $\Theta_4 = 1$

**3. Step Size: $\alpha$ = 0.01**

#### 3.3.4.1.1.2 Outputs

**1. Output Classes**

**a.** Home-maker (1) **b.** Daily-Commuter (2) **c.**Delivery person (3)

**2. Final Theta Values**

$\Theta_0 = 0.1206$ $\Theta_1 = -4.6406$ $\Theta_2 = -8.164$ $\Theta_3 = 4.8992$ $\Theta_4 = -2.2427$

**3. Cost Function**

Minimum value for 10000 iterations = 0.3629

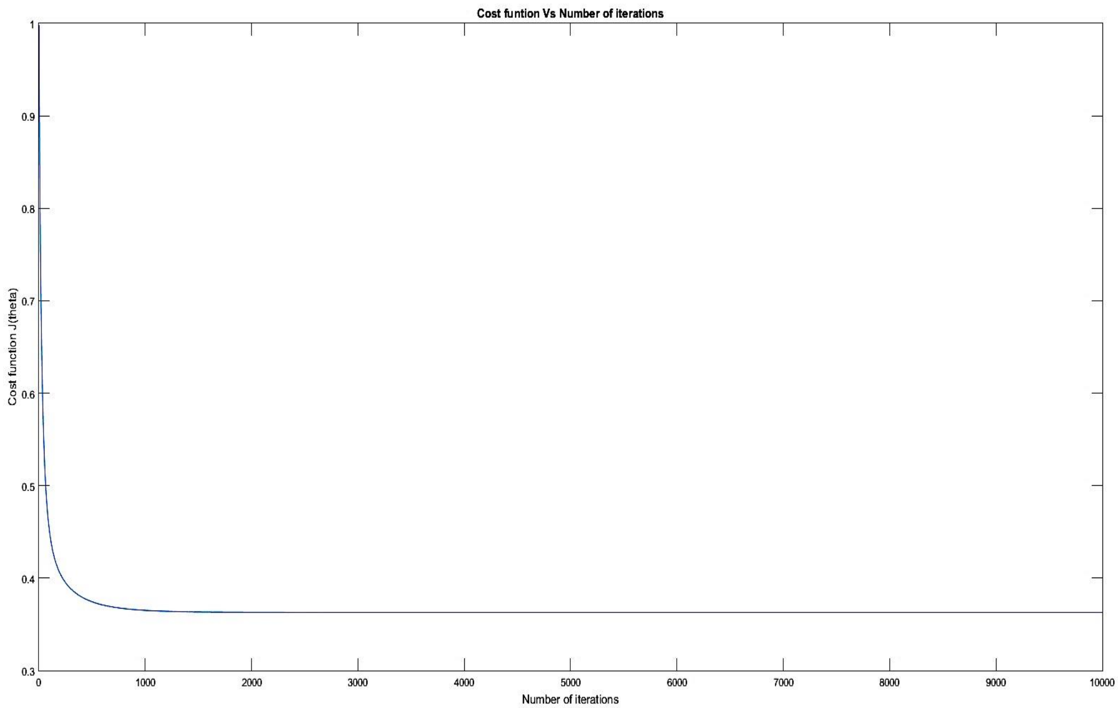


**Figure 3.30** **Classifier 2_1_1. Decreasing cost function with number of iterations**

#### 3.3.4.1.2 Classifier1_3_1

**(Classifier that separates class 1 and 3 with class 1 being the positive class)**

##### 3.3.4.1.2.1 Inputs

**1. Features**

**a.** Number of Instances of Battery Usage

**b.** Plug-In Frequency

**c.** Battery Consumption

**d.** Duration of Plug-In

**2. Initial Theta Values:**

$\Theta_0 = 1$ $\Theta_1 = 1$ $\Theta_2 = 1$ $\Theta_3 = 1$ $\Theta_4 = 1$

**3. Step Size: α = 0.01**

#### 3.3.4.1.2.2 Outputs

**1. Output Classes**

**a.** Home-maker (1) **b.** Daily-Commuter (2) **c.** Delivery person (3)

**2. Final Theta Values**

$\Theta_0 = 0.1206$ $\Theta_1 = -4.6406$ $\Theta_2 = -8.164$ $\Theta_3 = 4.8992$ $\Theta_4 = -2.2427$

**3. Cost Function:**

Minimum value for 10000 iterations = 0.0119

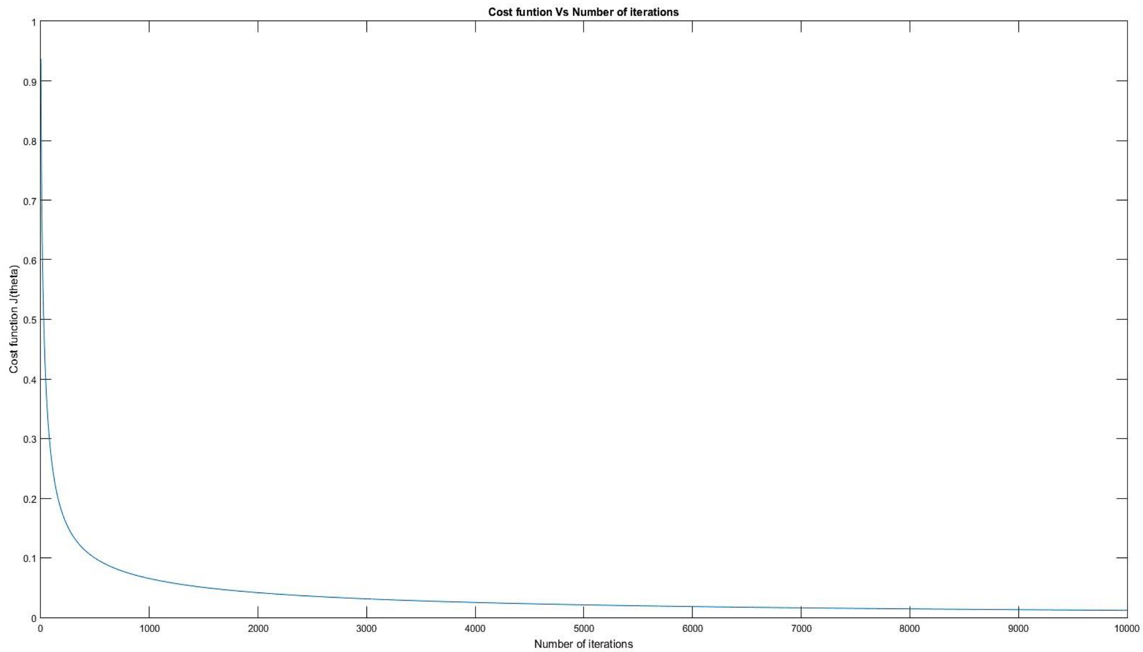


**Figure 3.31 Classifier 1_3_1. Decreasing cost function with number of iterations**

### 3.3.4.1.3 Classifier3_2_1

**(Classifier that separates class 3 and 2 with class 3 being the positive class)**

#### 3.3.4.1.3.1 Inputs

**1. Features**

a. Number of Instances of Battery Usage

b. Plug-In Frequency

c. Battery Consumption

d. Duration of Plug-In

**2. Initial Theta Values**

$\Theta_0 = 1$ $\Theta_1 = 1$ $\Theta_2 = 1$ $\Theta_3 = 1$ $\Theta_4 = 1$

**3. Step Size: $\alpha = 0.01$**

#### 3.3.4.1.3.2 Outputs

**1. Output Classes**

**a.** Home-maker (1) **b.** Daily-Commuter (2) **c.** Delivery person (3)

**2. Final Theta Values**

$\Theta_0 = 2.7002$ $\Theta_1 = -1.2141$ $\Theta_2 = -1.0015$ $\Theta_3 = 2.4875$ $\Theta_4 = 27.9840$

**3. Cost Function**

Minimum value for 10000 iterations = 0.0181

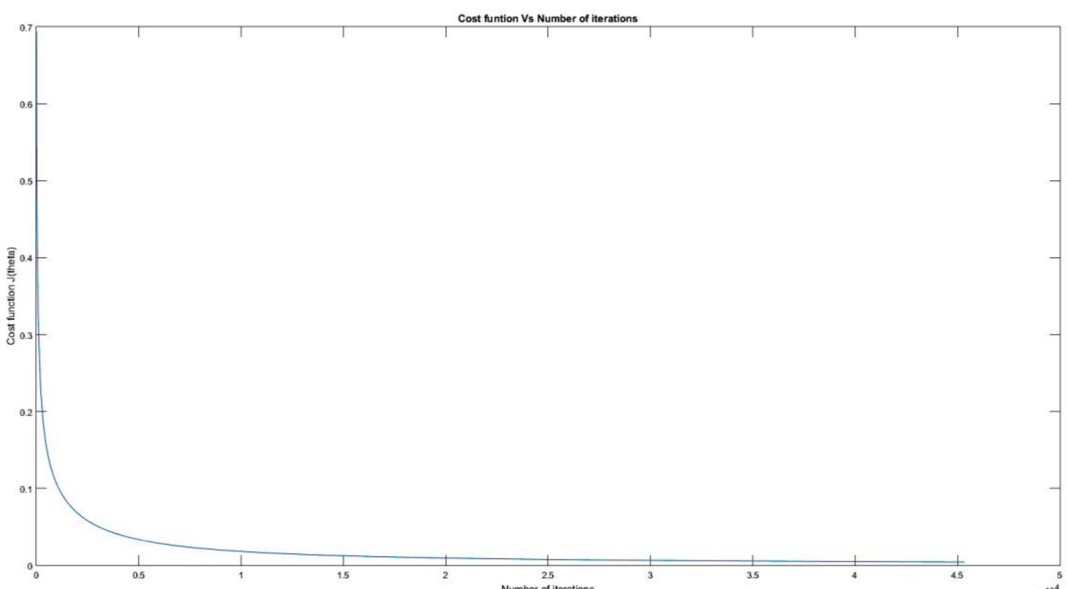


**Figure 3.32 Classifier 3_2_1. Decreasing cost function with number of iterations**

In order, to achieve higher generalizability, we have conducted 3 tests on the classification algorithm by introducing noise to a varying degree of low medium and high. This gives us the performance measure of the classifiers under 3 varying noise conditions. This helps in evaluating the best (least noise) and the worst case (High noise) conditions.

#### 3.3.4.1.4 Confusion Matrix (Test Data1 = Least Noise)

**Table 3.1 Confusion Matrix (Test Data1 = Least Noise)**

**a. Home-Maker**

| | | **Prediction** | |
|---|---|---|---|
| | | **0** | **1** |
| **Actual** | **0** | 27 | 5 |
| | **1** | 4 | 13 |
| Threshold = 0.5 | | | |

**Recall** = 76.47%

**Precision** = 72.22%

**F1 Score** = 0.74

**b. Delivery Person**

| | | **Prediction** | |
|---|---|---|---|
| | | **0** | **1** |
| **Actual** | **0** | 34 | 0 |
| | **1** | 0 | 15 |
| Threshold = 0.5 | | | |

**Recall** = 100%

**Precision** = 100%

**F1 Score** = 1

**c. Daily Commuter**

| | | **Prediction** | |
|---|---|---|---|
| | | **0** | **1** |
| **Actual** | **0** | 28 | 4 |
| | **1** | 5 | 12 |
| Threshold = 0.5 | | | |

**Recall** = 70.5%

**Precision** = 75%

**F1 Score** = 0.72

#### 3.3.4.1.4.1 Comments

1. The confusion matrix in Table 3.1 is calculated from a test data consisting of 49 samples. Each sample represents a day's driving characteristic of a profile.
2. From the above calculation of the confusion matrix and the F1 measure, we can deduce that the F1 score for the Delivery person class, which represents the service industry EV driving population, is high, which is an indication that, this class is easily identifiable compared to the other two.
3. The F1 score for the Homemaker and the Daily Commuter are comparable at 0.74 and 0.72 respectively. This tells us that the charging behaviors of these two classes are comparable and hence a slightly more complexity or data in model implementation is needed to achieve a higher F1 score.

#### 3.3.4.1.5 Confusion Matrix (Test Data2 = Medium Noise)

**Table 3.2 Confusion Matrix (Test Data2 = Medium Noise)**

**a. Home-Maker**

| | | Prediction | |
|---|---|---|---|
| | | **0** | **1** |
| **Actual** | **0** | 26 | 5 |
| | **1** | 15 | 0 |
| Threshold = 0.5 | | | |

**Recall** = 0%

**Precision** =0%

**F1 Score** = 0

**b. Delivery Person**

| | | Prediction | |
|---|---|---|---|
| | | **0** | **1** |
| **Actual** | **0** | 10 | 22 |
| | **1** | 7 | 7 |
| Threshold = 0.5 | | | |

**Recall** = 50%

**Precision** = 24.137%

**F1 Score** = 0.325

**c. Daily Commuter**

| | | Prediction | |
|---|---|---|---|
| | | **0** | **1** |
| **Actual** | **0** | 25 | 4 |
| | **1** | 9 | 8 |
| Threshold = 0.5 | | | |

**Recall** = 47.058%

**Precision** = 66.66%

**F1 Score** = 0.5517

#### 3.3.4.1.5.1 Comments

1. The above confusion matrix is calculated from a test data consisting of 46 samples. Each sample representing a day is driving characteristic of a profile.
2. From the above calculation of the confusion matrix and the F1 measure, we can deduce that there is a considerable reduction in the F Measure values. From this, we understand that Logistic Regression algorithms are more susceptible to noise.
3. This can be improved by employing outlier detection techniques to remove outliers before feeding them into the algorithms.

### 3.3.4.1.6 Confusion Matrix (Test Data 3 = High Noise)

**Table 3.3 Confusion Matrix (Test Data3 = High Noise)**

**a. Home-Maker**

| | | **Prediction** | |
|---|---|---|---|
| | | **0** | **1** |
| **Actual** | **0** | 12 | 27 |
| | **1** | 8 | 8 |
| Threshold = 0.5 | | | |

**Recall** = 50%

**Precision** = 27.58%

**F1 Score** = 0.3558

**b. Delivery Person**

| | | **Prediction** | |
|---|---|---|---|
| | | **0** | **1** |
| **Actual** | **0** | 36 | 4 |
| | **1** | 7 | 2 |
| Threshold = 0.5 | | | |

**Recall** = 22.22%

**Precision** = 33.33%

**F1 Score** = 0.2667

**c. Daily Commuter**

| | | Prediction | |
|---|---|---|---|
| | | **0** | **1** |
| **Actual** | **0** | 16 | 9 |
| | **1** | 19 | 5 |
| Threshold = 0.5 | | | |

**Recall** = 20.833%

**Precision** = 35.71%

**F1 Score** = 0.2632

#### 3.3.4.1.6.1 Comments

1. The above confusion matrix is calculated from a test data consisting of 49 samples. Each sample representing a day's driving characteristic of a profile.
2. From the above calculation of the confusion matrix and the F1 measure, the scores are comparable to one another.
3. The F1 score for the Homemaker, Delivery person and Daily commuter classes are significantly less compared to the previous trials. This is clear indication that the logistic regression classifier performs poorly in the presence of high noise in the dataset. We can improve this performance by using better classifiers like Support Vector Machines and employing outlier detection techniques.

#### 3.3.4.1.7 Summary of results

**Table 3.4 Summary of Test Results**

| | Test 1<br>Best Case<br>Less Noisy Data | | | Test 2<br>Average Case<br>Medium Noisy Data | | | Test 3<br>Worst Case<br>High Noisy Data | | |
|---|---|---|---|---|---|---|---|---|---|
| **Class** | **Precision** | **Recall** | **F measure** | **Precision** | **Recall** | **F measure** | **Precision** | **Recall** | **F measure** |
| **1** | 0.722 | 0.764 | 0.740 | 0 | 0 | 0 | 0 | 0 | 0 |
| **2** | 0.75 | 0.70 | 0.720 | 0.666 | 0.470 | 0.551 | 0.091 | 0.077 | 0.088 |
| **3** | 1 | 1 | 1 | 0.241 | 0.500 | 0.325 | 0 | 0 | 0 |
| **Average F measure** | 0.820 | | | 0.355 | | | 0.029 | | |

### 3.3.4.1.7.1 Comments

**1.** The Table 3.4 represents the summary of the test results with different levels of noise.

**2.** We use 1 data point per day to represent the charging characteristics of a profile. So, less information pertaining to each profile (for ex. Home – maker's frequent charge and discharge characteristic – a distinguishable factor from the other two profiles- is not apparent) is available. The classifier assumes that the home – maker and the delivery person to have similar information based on similar battery usage.

**3.** When additional noise – in the form of random data - is added from best case to average case the classifier has less information to classify the profiles as we use 1 data point/day. Hence, it readily outputs lesser precision and recall values for both home – maker and delivery person, which appear to be similar owing to their battery consumption.

**4.** As we move into the high noisy data – introduced by changing the profile labels (for ex. Delivery person's label changed to home – maker etc.) the values correspondingly decrease further.

#### 3.3.4.2 Fuzzy Logic Approach

The following design considerations are made to classify the data into different classes. They are presented with each subsequent consideration being an improvement over its predecessor.

##### 3.3.4.2.1 1-hour interval

The initial design consideration was to sample data at an hourly basis. However, to successfully classify profiles on the said basis, we created rules for each hour. This unnecessarily increased the complexity of the Fuzzy Inference system, as charging characteristics of profiles at an hourly resolution would not give us enough details to perform a successful classification. Hence, two other approaches were considered, wherein, **1.** The data for an entire day would be divided into 5 sections **2.** Cumulative data was collected for an entire day to perform a classification.

##### 3.3.4.2.2 5 sections throughout a day

The following assumptions are made about the features before implementing them in the 5 sections a day FIS (Fuzzy Inference System).

1. **Time feature:** The day is divided into 5 sections, namely, Early-Morning (12am to 4am), Morning (4am to 11am), Afternoon (11am to 4pm), Evening (4pm to 8pm), and Night (8pm to 12 am).

   From the charging data, we infer that the charging characteristics of all the profiles remain the same late night and “Early-morning”. However, the charging characteristics will differ significantly in the “Morning”, “Afternoon” and “Evening” time slots. Hence, we use these three timeslots for our Fuzzy Inference Rules.

   Each feature row is decided by combining the data of four time-stamps.

   DP (1, :) = [4, 0, 0, 0];

   DP (2, :) = [11, 0, 14, 120];

   DP (3, :) = [16, 0, 28, 300];

   DP (4, :) = [20, 1, 14, 120];

   DP (5, :) = [24, 1, 0, 0];

2. **Battery usage:** The Home-maker class has low and medium usage whereas Delivery Person will have high and medium usage.

3. **Plug-In Number:** Daily-commuter and Delivery-person will have low and medium “Plug – In Number” whereas home-maker will have a “High” Plug – In Number.

4. **Duration of Plug-Out:** Daily commuter and Delivery person will have a longer Duration of Plug – Out whereas home – maker class will have a low duration of plug - out.

#### 3.3.4.2.2.1 Implementation

The following data points represent the 5 inputs given to the FIS:

IN1(1, :) = [10, 1, 10, 120];

IN1(2, :) = [12, 2, 3, 60];

IN1(3, :) = [16, 3, 10, 60];

IN1(4, :) = [20, 4, 11, 120];

IN1(5, :) = [24, 4, 0, 0];

**Output: Homemaker**

Further, we observed that even if there was a change in the length of inputs the FIS made the right decisions. Hence, we infer that the Fuzzy Inference System can be a robust system, whose performance is independent of the number of inputs given to it.

IN2(1, :) = [19, 1, 25, 600];

IN2(2, :) = [24, 1, 0, 0];

IN2(3, :) = [5, 0, 0, 0];

**Output: Daily-commuter**

IN3(1, :) = [12, 1, 40, 180];

IN3(2, :) = [18, 2, 20, 240];

IN3(3, :) = [24, 2, 0, 0];

**Output: Delivery-person**

The outputs generated from each of the input data point are combined to unearth the final output. Consequently, genfis3 which generates fuzzy inference system from data using fuzzy c-means clustering was implemented.

fismat = genfis3(Xin, Xout,'mamdani');

Fuzzy C-Means Clustering takes a dataset and a desired number of clusters and returns optimal cluster centers and membership grades for each data point.

In our case, Xin is an input dataset which has fixed number of features (columns), but variable number of data instance throughout day (rows). Xout is output for different input data points (rows) in 3 membership profiles.

The implementation is as shown below:

```
% read fuzzy inference system model
    Model = readfis('EV_FIS_trapFunction');
% evaluate fuzzy inference system model output for given input
    Xout = evalfis (Xin, Model);
```

And then genfis3 is called:

```
fismat = genfis3(Xin, Xout, 'mamdani');
```

From fismat variable, I received all (3) clusters range as below:

```
outputRange(1,:) = fismat.output(1).range;
outputRange(2,:) = fismat.output(2).range;
outputRange(3,:) = fismat.output(3).range;
```

Using this method, different clusters have been created and based on the 3 output profiles, each cluster will return a membership function value for the respective class (profile). The highest membership function from each of the output profile, will be selected for the day.

A minimum of 3 input rows (data points) are needed to achieve clear distinguishability, for each cluster.

The following fuzzy inference methods are used by genfis3 to produce the aggregate output.

**Table 3.5 Fuzzy Inference Methods used by genfis3**

| **Inference Method** | **Default** |
|---|---|
| AND | prod |
| OR | probor |
| Implication | prod |
| Aggregation | sum |
| Defuzzification | wtaver |

#### 3.3.4.2.3 1 data point per day

A different feature set has been used for this case:

**1.** Plug-in Time per day: Data type - float

**2.** Battery usage per day (only discharging): Data type - float

**3.** Number of Plug-ins per day: Data type - Integer

**4.** Number of battery discharge: Data type - Integer

Example. A UPS driver services 200-300 delivery points in a day. Each of these delivery points require a stop and start mechanism, which implies that there is a battery usage at each sequence. So, if we exclude the stops at the traffic lights etc. The number of delivery points, itself is a relatively high number corresponding to a high number of battery usage.

### 3.3.4.2.3.1 Fuzzy Inference System

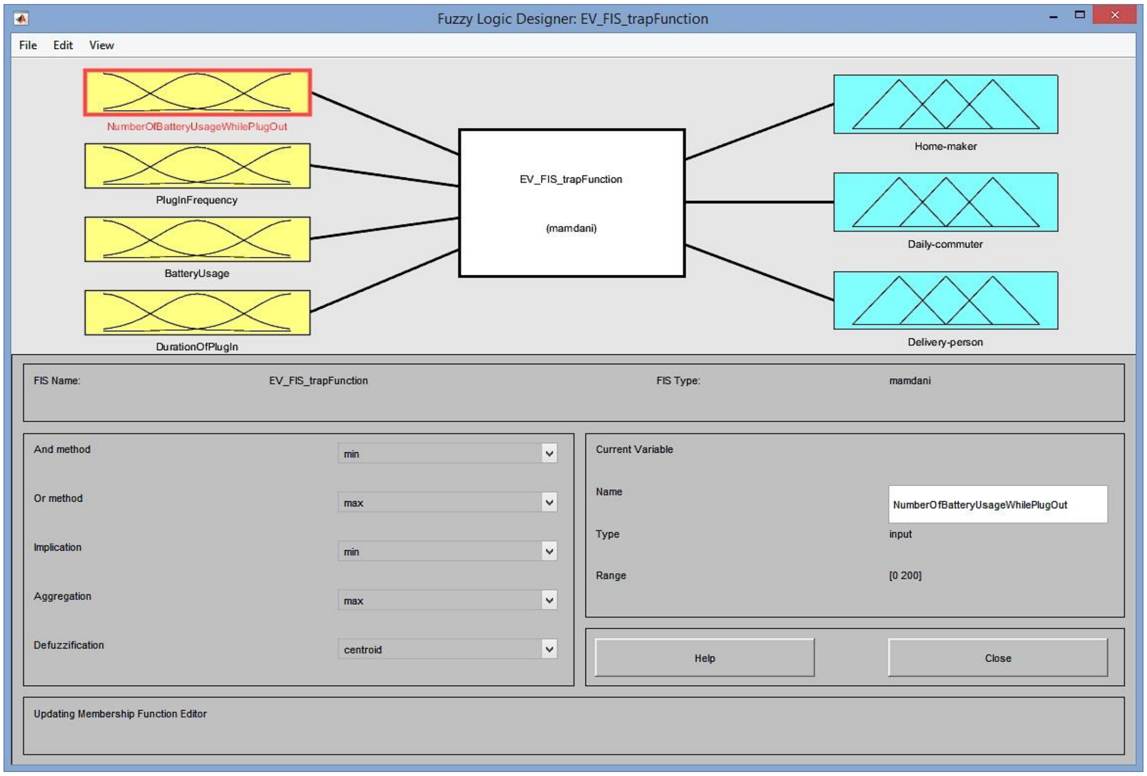


**Figure 3.33 Overall View of Fuzzy Logic Design**

The following screenshots represent the membership functions:

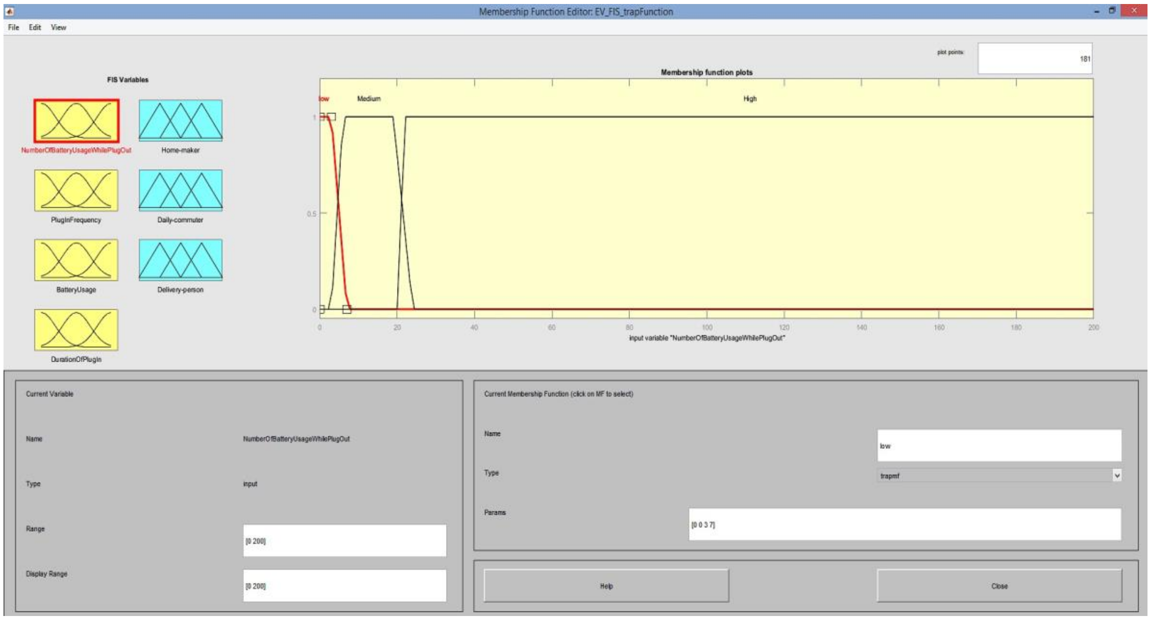


**Figure 3.34 Frequency of battery discharge**

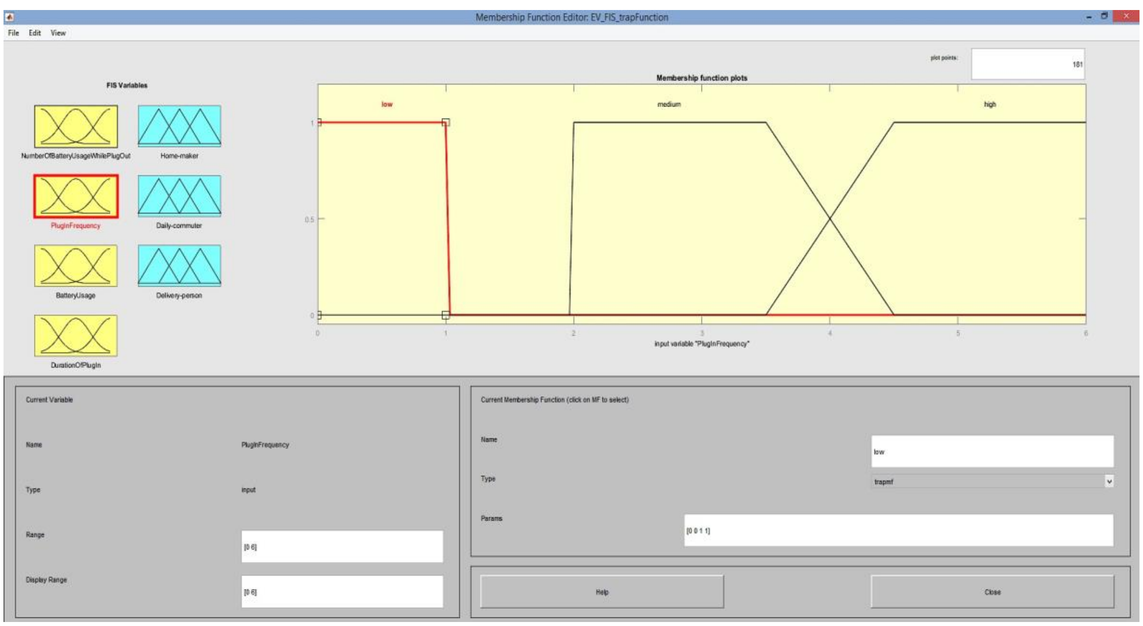


**Figure 3.35 Number of Plug-In**

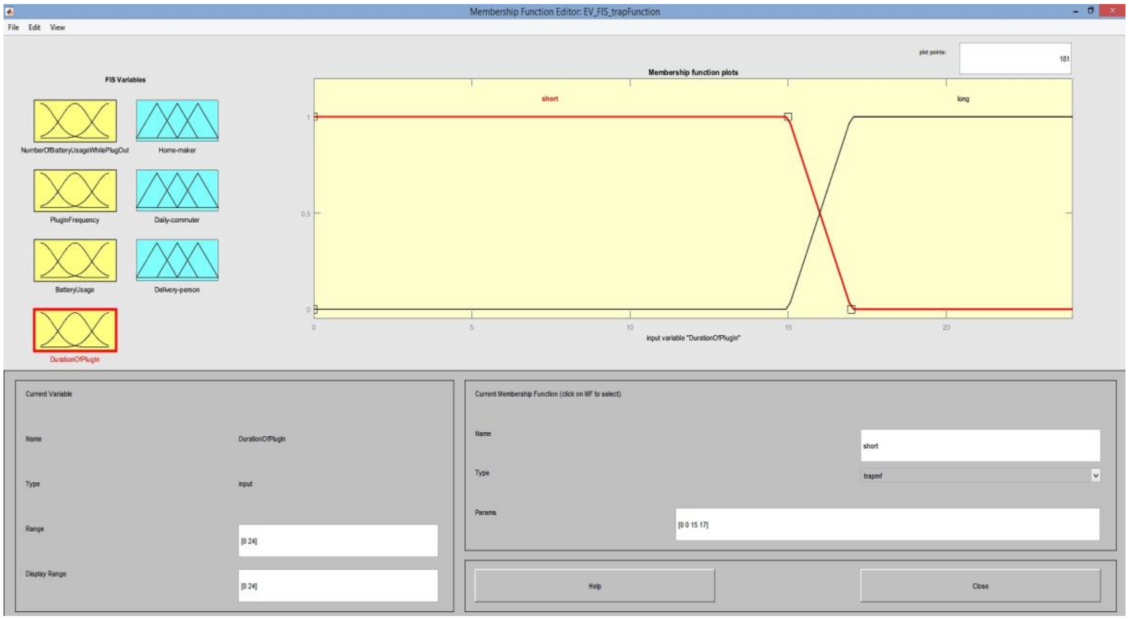


**Figure 3.36 Duration of Plug-In**

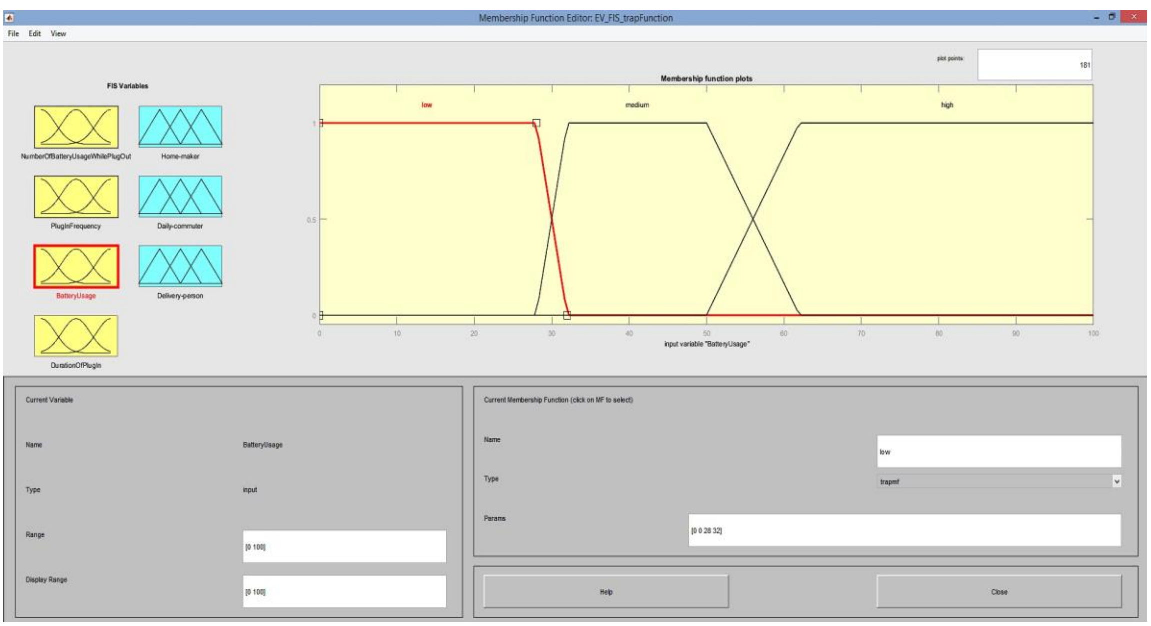


**Figure 3.37 Battery Usage**

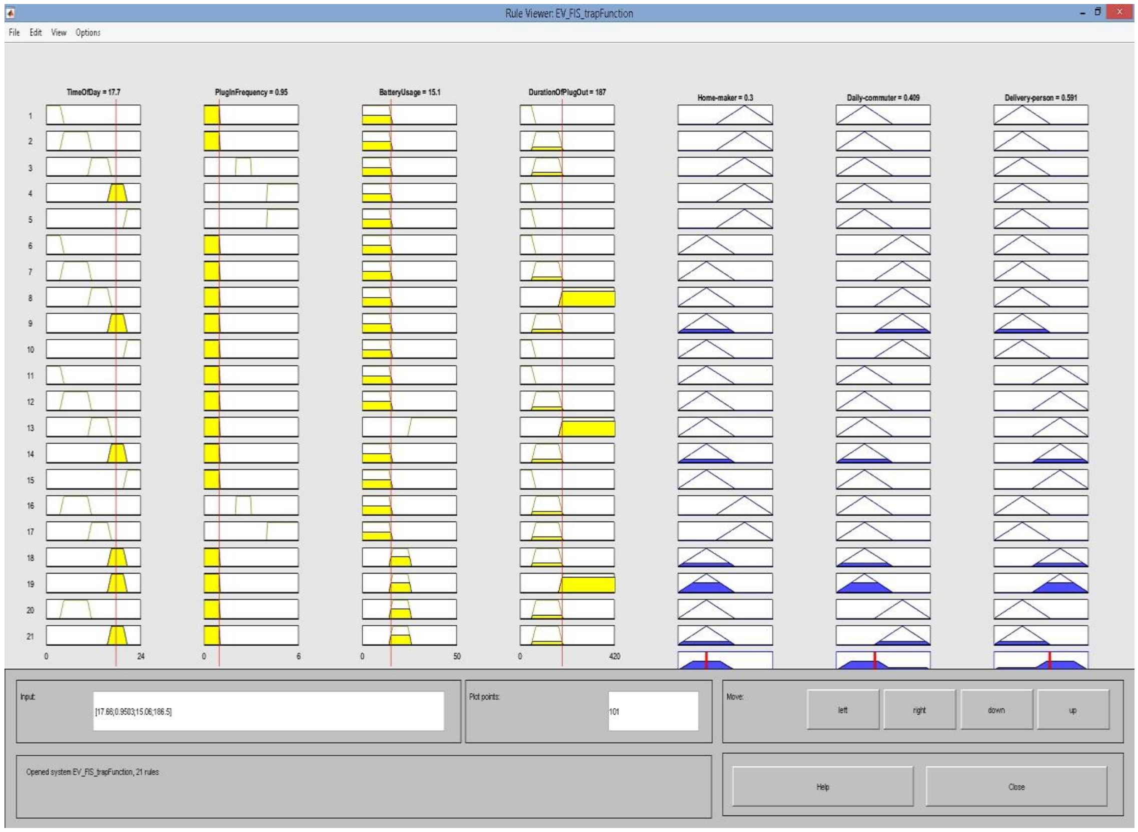


**Figure 3.38 Implementation with same logistic regression training data**

### 3.3.4.2.3.2 Confusion Matrix

To evaluate the performance of the fuzzy inference system used above we have implemented the following confusion matrix. The evaluation is conducted based on the F1 score or the F measure.

**Table 3.6 Confusion matrix representation**

| | | Predicted | | |
|---|---|---|---|---|
| | | **Home-maker** | **Daily Commuter** | **Delivery Person** |
| **Actual** | **Home-maker** | **10** | **0** | **0** |
| | **Daily Commuter** | **2** | **11** | **0** |
| | **Delivery Person** | **3** | **0** | **9** |

| | | Predicted | |
|---|---|---|---|
| | | **Not Home-maker** | **Home-maker** |
| **Actual** | **Not Home-maker** | **20** | **5** |
| | **Home-maker** | **0** | **10** |

| | | Predicted | |
|---|---|---|---|
| | | **Not Daily Commuter** | **Daily Commuter** |
| **Actual** | **Not Daily Commuter** | **22** | **0** |
| | **Daily Commuter** | **2** | **11** |

| | | Predicted | |
|---|---|---|---|
| | | **Not Delivery Person** | **Delivery Person** |
| **Actual** | **Not Delivery Person** | **23** | **0** |
| | **Delivery Person** | **3** | **9** |

| | Precision | Recall | F measure |
|---|---|---|---|
| **Home-maker** | **0.1666** | **1** | **0.7999** |
| **Daily Commuter** | **1** | **0.8461** | **0.9166** |
| **Delivery Person** | **1** | **0.75** | **0.8571** |

Average F measure = 0.8578

#### 3.3.4.2.3.2.1 Comments

From the F measure as shown in the above Tables we infer that the F-measure is the highest for the Daily commuter class. From this we infer that the Daily Commuter class is highly distinguishable by the Fuzzy inference system.

### 3.3.4.2.4 Implementation and change in FIS with test data used in logistic regression

This implementation is to avoid cases where it cannot predict output from any of profiles.

**Table 3.7 Implementation and change in FIS with test data used in logistic regression**

| Output Profile | # of battery usage while Plug-Out per day | | Battery Consumption per day | | Plug-In Frequency per day | | Total Plug-In time per day |
|---|---|---|---|---|---|---|---|
| Home-maker | Low | and | Low | and | Low | and | Short |
| | Medium | | Medium | | High | | Long |
| | Medium | | Low | | Medium | | Long |
| | Medium | | Medium | | Medium | | Long |
| Daily Commuter | Low | and | Low | and | Low | and | Short |
| | | | Medium | | Medium | | |
| | | | Medium | | Low | | |
| | | | Low | | Medium | | |
| | High | and | High | and | Low | and | Short |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Delivery Person** | | | | | Medium | | |

### 3.3.4.2.5 Fuzzy Rules

The below case illustrates the implementation of the Fuzzy rules created from the Table 3.7.

Example. Daily-commuter

#### 3.3.4.2.5.1 Input Features

1. Number of battery usage while Plug-Out time = 6
2. Number of Plug-ins per day = 3
3. Battery usage per day (only discharging) = 54
4. Plug-in Time per day = 13

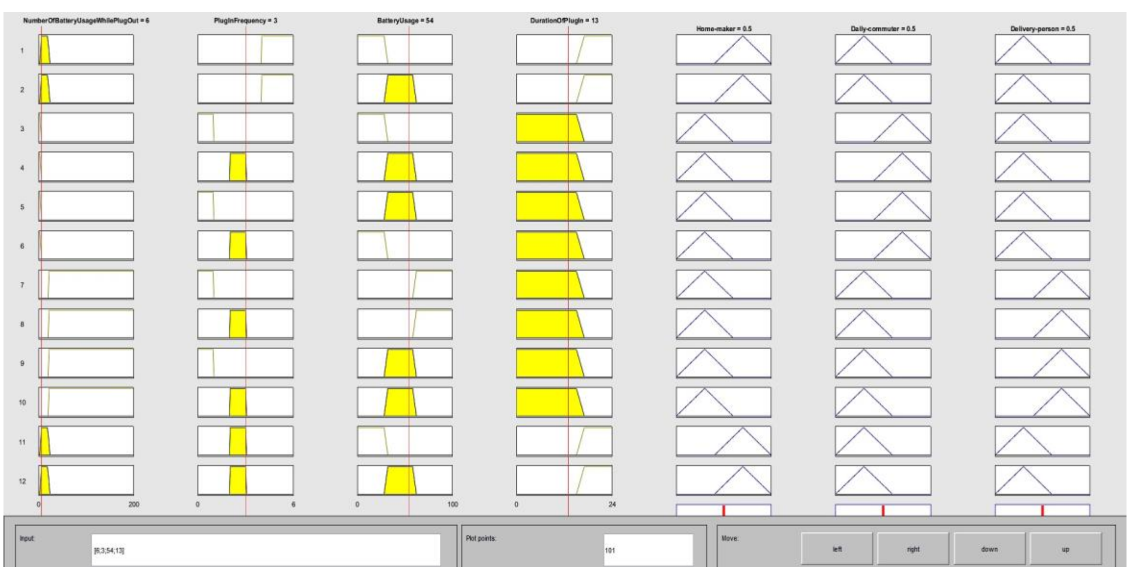


**Figure 3.39 Problem in identifying inference rule for case [6 3 54 13]**

**Problem:** From the above Table, we infer that none of the output classes are triggered.

This is attributed to the lack of rules governing the extra cases.

**Solution:** Add additional rule to improve the classifier as shown in Table 3.4

**Table 3.8 Solution to improve classifier**

| Output Profile | # of battery usage while Plug-Out per day | Plug-In Frequency per day | Battery Consumption per day | Total Plug-In time per day |
|---|---|---|---|---|
| **Daily Commuter** | **Medium** | **Medium** | **Medium** | **Long** |

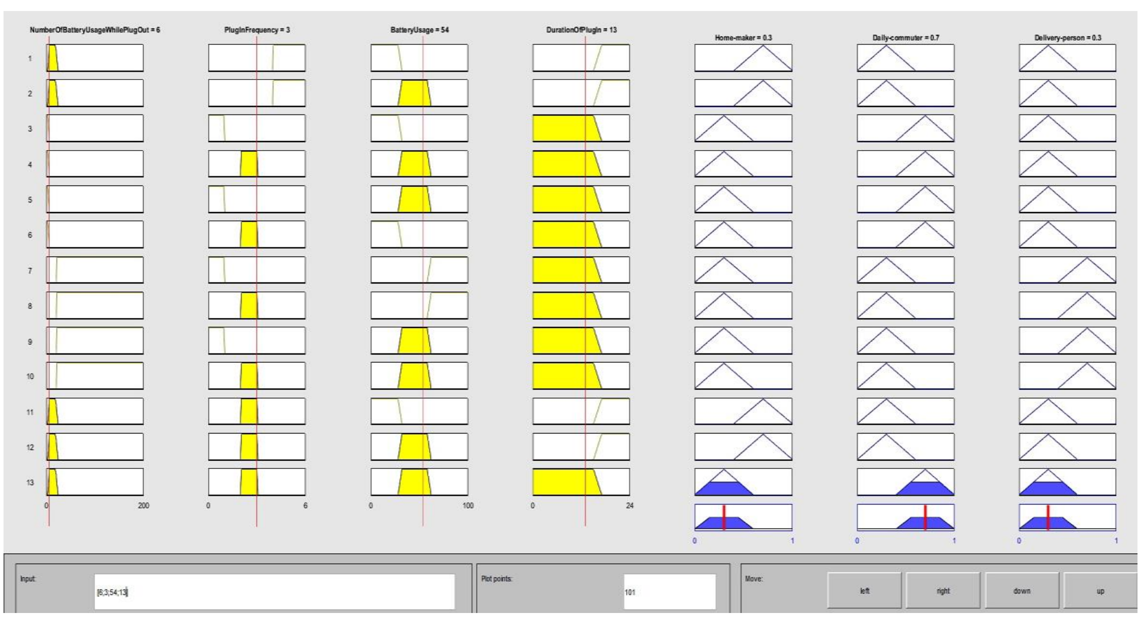


**Figure 3.40 Problem in identifying inference rule for case [6 3 54 13]**

Post addition of corrective rules to the model on test data, there were some points where it cannot classify irrespective of the profiles. Hence, more number of fuzzy inference rules may be required or degree of fuzzy membership needs to be changed according to given test data, which can correctly classify for all cases.

For example, there is a data point with [55 1 52.166 8.145]. From given membership values for features given below, it caused error of not classifying in any classes because of lack of rule firing. There are 2 reasons for the misclassification: **1.** Lack of number of rules and other. **2.** Misjudging degree of membership function for one of the feature.


**Figure 3.41** **No rule is fired for input [55 1 52.166 8.145] to judge output profile**

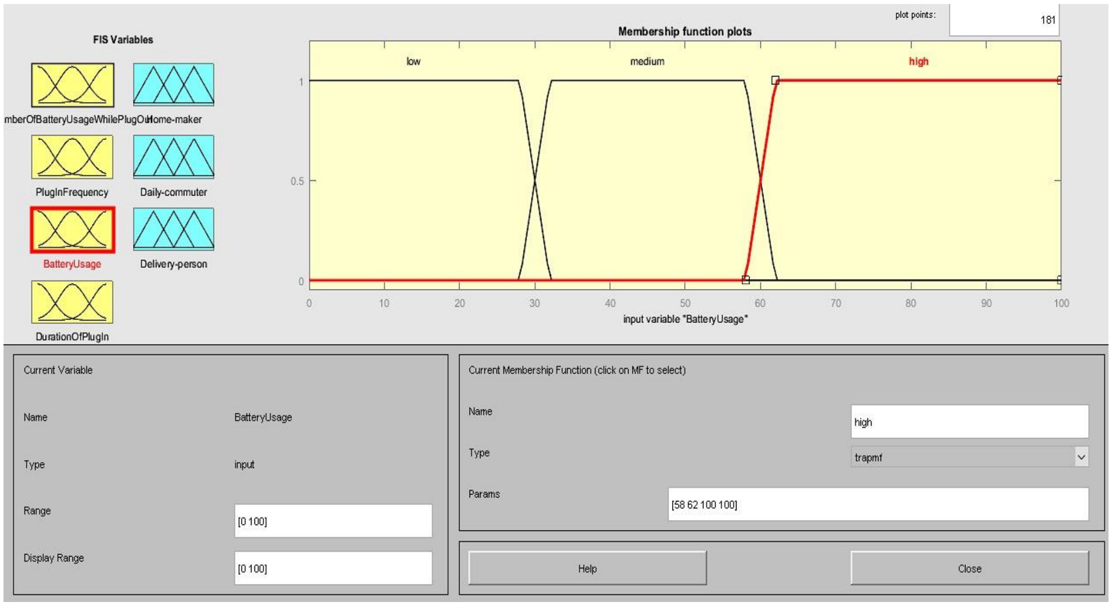


**Figure 3.42 Degree of membership for "Battery Usage" feature**

[55 1 52.166 8.145] case belongs to delivery person`s profile. However, from Figure 3.42 given above, degree of membership starts at 58, which limits high battery usage case.

To solve this problem, the membership is changed so that it matches the output.

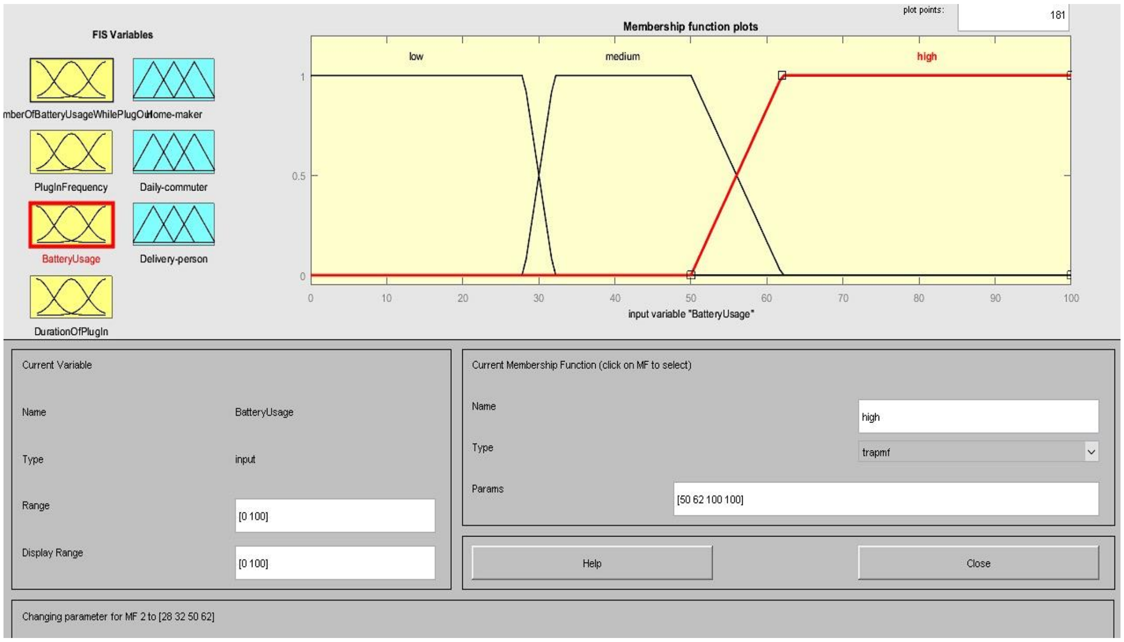


**Figure 3.43** Changed degree of membership of "Battery Usage" feature

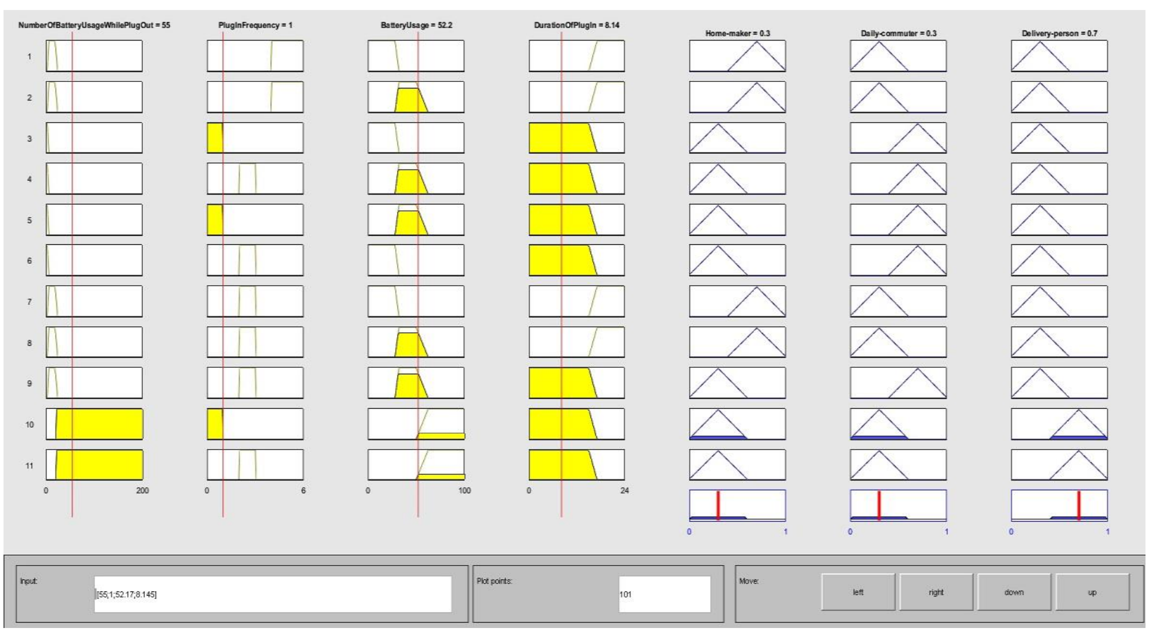


**Figure 3.44** Rules get fired for case [55 1 52.166 8.145] or relevant cases

From Figure 3.44 it is evident that the rules get fired for the case [55 1 52.166 8.145]. Hence, we solve the problem.

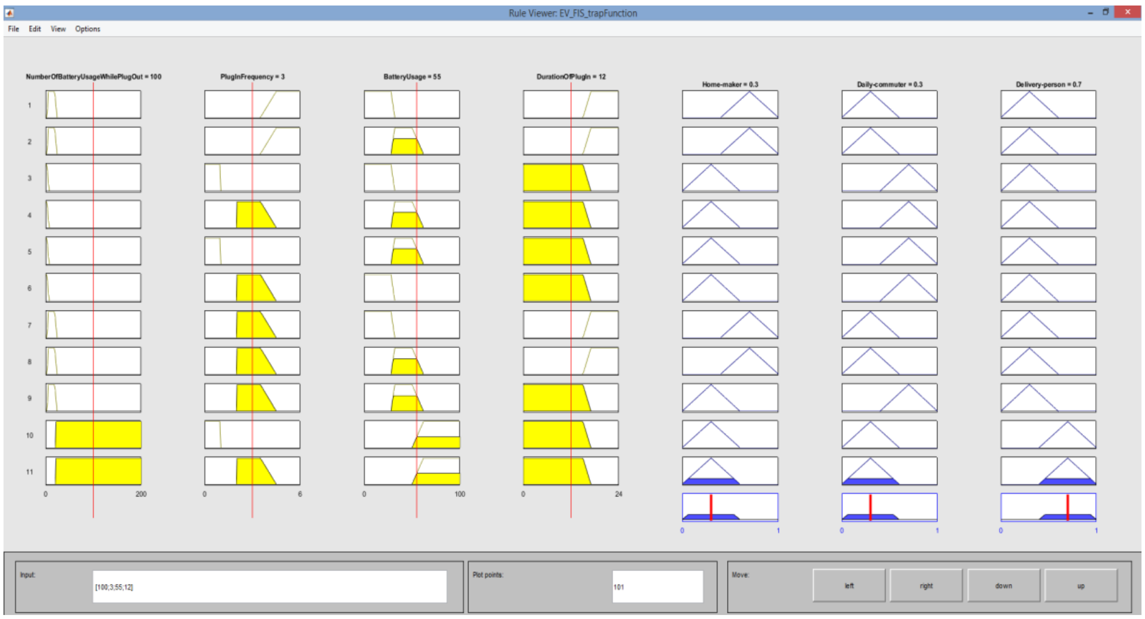


**Figure 3.45 Final view of fuzzy inference rules**

**Table 3.9 Calculation of F measure under Less Noisy conditions**

**Test 1: (less noise) Data size = 80**

| | | **Predicted** | | |
|---|---|---|---|---|
| | | **Home-maker** | **Daily Commuter** | **Delivery Person** |
| **Actual** | **Home-maker** | **25** | **2** | **0** |
| | **Daily Commuter** | **0** | **27** | **0** |
| | **Delivery Person** | **0** | **0** | **26** |

| | | Predicted | |
|---|---|---|---|
| | | **Not Home-maker** | **Home-maker** |
| **Actual** | **Not Home-maker** | **25** | **2** |
| | **Home-maker** | **0** | **53** |

| | | Predicted | |
|---|---|---|---|
| | | **Not Daily Commuter** | **Daily Commuter** |
| **Actual** | **Not Daily Commuter** | **27** | **2** |
| | **Daily Commuter** | **0** | **51** |

| | | Predicted | |
|---|---|---|---|
| | | **Not Delivery Person** | **Delivery Person** |
| **Actual** | **Not Delivery Person** | **26** | **0** |
| | **Delivery Person** | **0** | **54** |

| | Precision | Recall | F measure |
|---|---|---|---|
| **Home-maker** | **0.9636** | **1** | **0.9814** |
| **Daily Commuter** | **0.9622** | **1** | **0.9807** |
| **Delivery Person** | **1** | **1** | **1** |

**Average F measure = 0.9873**

#### 3.3.4.2.6 Test 2: (Medium noise) data size = 46

**Table 3.10 Calculation of F measure under Medium Noise conditions**

| | | Predicted | | |
|---|---|---|---|---|
| | | **Home-maker** | **Daily Commuter** | **Delivery Person** |
| **Actual** | **Home-maker** | **9** | **5** | **0** |
| | **Daily Commuter** | **2** | **15** | **0** |
| | **Delivery Person** | **0** | **1** | **10** |

| | Precision | Recall | F measure |
|---|---|---|---|
| **Home-maker** | **0.6429** | **0.8182** | **0.7200** |
| **Daily Commuter** | **0.7143** | **0.8824** | **0.7895** |
| **Delivery Person** | **1** | **0.9091** | **0.9524** |

**Average F measure = 0.8206**

##### 3.3.4.2.6.1 Comments

1. The above case represents the performance of the classifier for medium noise level data.
2. This evaluation is needed to check the robustness of the algorithm, when fed with noisy data.

### 3.3.4.2.7 Test 3: (High noise) data size = 48

**Table 3.11 Calculation of F measure under High Noise conditions**

| | | Predicted | | |
|---|---|---|---|---|
| | | **Home-maker** | **Daily Commuter** | **Delivery Person** |
| **Actual** | **Home-maker** | **0** | **17** | **15** |
| | **Daily Commuter** | **14** | **2** | **0** |
| | **Delivery Person** | **0** | **0** | **0** |

| | **Precision** | **Recall** | **F measure** |
|---|---|---|---|
| **Home-maker** | **0** | **0** | **0** |
| **Daily Commuter** | **0.1053** | **0.1250** | **0.1142** |
| **Delivery Person** | **0** | **0** | **0** |

**Average F measure = 0.0381**

#### 3.3.4.2.7.1 Comments

1. We infer from Table 3.7. that the average F- measure for data of size 48 is very low compared to the other two cases.
2. This high level of noise in the data was created by exchanging the labels of the existing test data to represent the high noise in the data.

#### 3.3.4.2.8 Possibilities to improve F measure (accuracy in prediction):

1. Change membership of features and output profile.
2. Modify/add additional rules, which have minimum or no effect on best-case scenario.

### 3.3.5 Scheduler

The scheduler is responsible for preparing the charging plan based on the selected profile information from the classifier. The motivation for the scheduler is to spread the charging load throughout the day, to prevent the contribution of EV charging to demand peaks. In this section, we present the rationale behind the creation of charging plans corresponding to the individual profiles.

#### 3.3.5.1 Profile: Home – maker

The charging plan for this profile mainly takes place during the day as maximum usage of EV takes place during maximum availability of solar energy. Consequently, to harness this renewable energy, the scheduler proposes the following charging plan. The departure time from the profiler in this case is assumed to be 15:00, as shown in Figure 3.50.

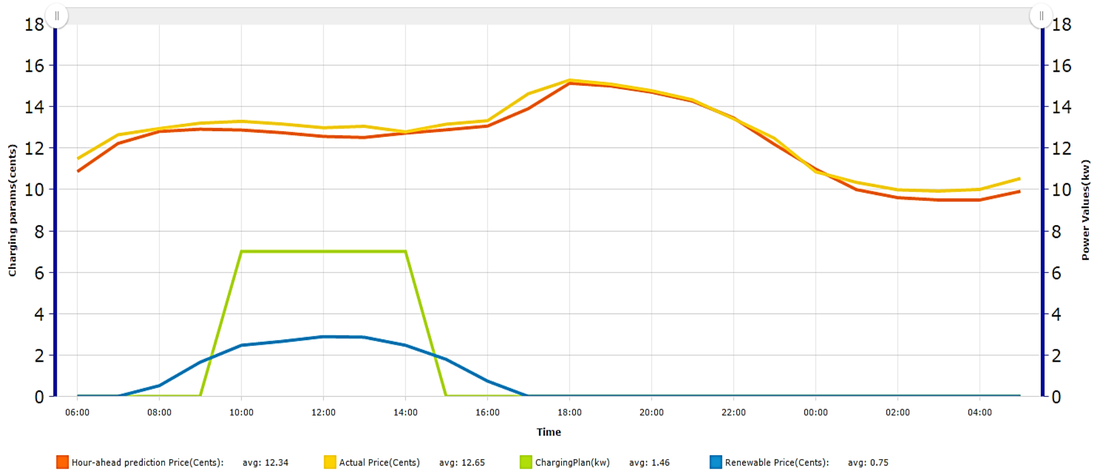


**Figure 3.46 Proposed home – maker charging schedule**

### 3.3.5.2 Profile: Regular commuter

For this profile, the charging does not have to take place frequently as the number of miles driven daily is less. So, we propose the EV to charge only if the battery goes below a certain threshold. We schedule the charging of this profile during late night or early morning, when there is minimal load. In this case, we infer from the hour ahead predicted price curve that the cost of charging is minimum at 2:00AM. The following graph Figure 3.51 presents the case.

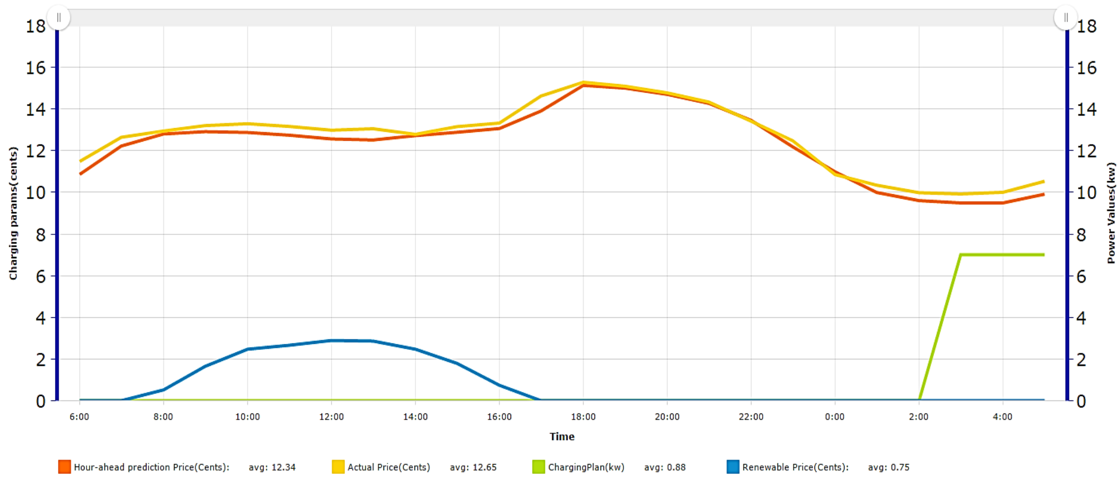


**Figure 3.47 Proposed Regular commuter charging schedule**

### 3.3.5.3 Profile: Delivery person

For this profile, the charging must be frequent, irrespective of the charging curve, as it represents power user base of the driving population. So, the charging must be scheduled as soon as the vehicle gets back home irrespective of the threshold and demand. Figure 3.52. represents the idea.

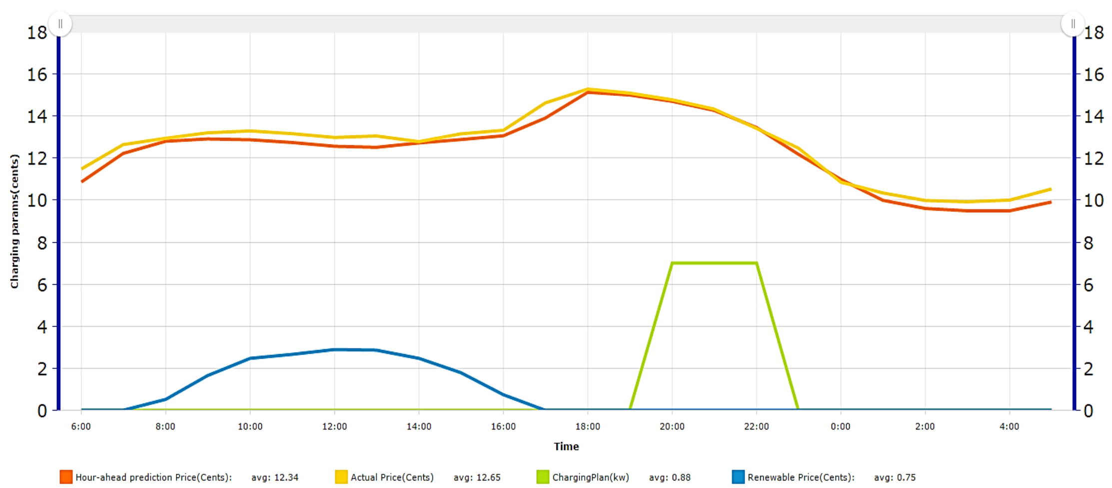


**Figure 3.48 Proposed Delivery person charging schedule**

**Note:** Even though the delivery person and the regular commuter profiles may charge at the same time the frequency of charging of the typical regular commuter is far less than that of the typical delivery person profile.

# Chapter 4. Conclusions and Future Work

## 4.1 Conclusions

We envision smart charging technologies as a synchronizing mechanism to match the higher rate of EV penetration with a relatively slower expansion rate of the grid. It creates a win-win situation for all participants in Energy production and consumption. Our man aim through this thesis is to use this synchronization mechanism to 1. Create economic value for consumers 2. Improve user – convenience 3. Help utilities in load management. 4. Create a profiling strategy for autonomous charging mechanism that blends into autonomous driving cars. This section explains some of the conclusions we can draw from our experimentation:

**1**. From Table 2.2 we infer that the cost of normal charging is 510.19 cents (5.10 USD), which is greater by 152.59 cents (1.52 USD) when compared to charging with smart charging algorithm i.e. 357.60 cents (3.57 USD). If we consider an EV with 30kWh battery and charges once every day to full battery capacity for 365 days, the total savings is (1.52 * 365 = 554.8 USD) which is considerable savings for an individual or a transportation based service company. This proves that the smart charging strategy creates economic value for customers and customers in the transportation industry.

2. From Figure 2.5 we infer that even though the charging period was set between 06:00pm to 05:00am, due to smart charging the EV does not begin charging until 10:30pm, the time at which the cost of the energy is minimum. This provides an excellent opportunity for the utilities to use time of use (ToU) mechanism to spread the charging of the EVs. This helps in managing the load on the grid and reduces peaks and prevents blackout.

3. From chapter 3 we have successfully demonstrated that machine learning algorithms like logistic regression and fuzzy logic can be used to create a profile the charging characteristics of EV users to prepare a more personalized charging plan (see section 3.2.5.) that caters to the specific driving needs of the customers. Further, it prevents the unnecessary charging of EV batteries and helps in extending their lifespan. More importantly, it revolutionizes our concept of driving and charging by removing human element, which is the weakest link in the process.

## 4.2 Future Work

### 4.2.1 Improving User/Driver Profiling

A combination of big data, deep learning cross different data sets including, e.g., text calendar/txt/social media, and context aware computing technologies can be used to leverage both structured and unstructured data generated by EV users to create richer and more accurate profiles to personalize driving/charging or other activities. The following cases better illustrate the above claim:

**Case 1:** In case of smart charging the Twitter/Facebook/calendar data of people can be analyzed to understand their transportation needs. For example, an EV owner has a dentist appointment tomorrow, where the dentist office is 30 miles away from his/her regular commute area, the car can retrieve this information from the owner's calendar/social media post and prepare a charging plan, so that the total charge accommodates the added unusual travel schedule.

**Case 2:** If a patient has a heart condition or suffering from a life-threatening disease, the car can analyze the medical history of this patient and charge itself to a higher percentage of SOC (State of Charge). By doing so it can ensure there is enough electric energy in the battery if care-giver/nurse of the patient must drive him/her to the medical center. Further, if we envision an autonomous future, the car itself can drive this person to the hospital with the extra electric energy.

### 4.2.2 Dealing with Security Threats

#### 4.2.2.1 Malicious Cyberattacks

The two-way communication between the EV and the grid could result in increasing the potential for security threats like malicious cyber-attacks. There is a high probability of creating miscommunication between the charging station and the EV by manipulating either of them to create unnecessary peaks in the grid infrastructure. This could affect the charging habits of other EVs connected to the same distribution grid and result in a total failure leading to a national security threat.

#### 4.2.2.2 Need for complex monitoring systems to detect or predict potential security threats

As the penetration of EVs increase, the amount of data flow between the EVs and the charging stations and servers of the utilities increase. Consequently, we will need a secure monitoring system that can understand the messages transmitted between the EV-Charging Station-Utility communication system and detect/predict security threats in advance and neutralize them.

### 4.2.3 Mitigate Structural Defects at Power Distribution Networks

Turning on a 240-volt AC level - 2 charger, as defined by the Society of Automotive Engineers is equivalent of adding three homes worth of electrical energy consumption to a neighborhood. The street-level transformers which supply electricity to these charging stations are designed to cool at night, as there is minimal usage. However, if the utilities charge a lower tariff to encourage EV owners to charge at night, this could lead to lesser cool-off times for the transformers. Thus, the copper windings of the transformer heat up, causing a short circuit and result in a black out. Additionally, coal, diesel and other greenhouse gas emitting fossil fuels are burnt to generate energy at night. This well-to-wheel carbon emissions can offset the zero emissions of the electric vehicles, their strongest selling point, and nullify their benefits. To overcome these potential disadvantages, there is a strong need to integrate wind farms that can contribute most the energy needs at night[22].

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