Smart Charging with Hourly Pricing: Reducing Costs and Grid Congestion for Promoting Electric Vehicles in Pakistan

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LIST OF ABBREVIATIONS

RES	Renewable Energy Sources
PEVs	Plug in Electric Vehicles
EV	Electric Vehicle
V2G	Vehicle to Grid
G2V	Grid to Vehicle
SoC	State of Charge
DSO	Distribution System Operator
TSO	Transmission System Operator
DISCO	Distribution Company
PRECON	Pakistan Residential Electricity Consumption
LESCO	Lahore Electric Supply Company
NEPRA	National Electric Power Regulatory Authority
NPCC	National Power Control Center
OPF	Optimal Power Flow

ABSTRACT

This study explores how smart charging with dynamic hourly pricing can address grid congestion concerns arising from the growing adoption of electric vehicles (EVs) in Pakistan. We propose an optimization technique to establish an hourly pricing model for Pakistani distribution companies, promoting off-peak charging behavior among EV owners. An agent-based energy management system is then introduced to facilitate coordination between EV aggregators and the grid. This system employs machine learning to accurately predict battery state-of-charge and integrates both grid-to-vehicle (G2V) and vehicle-to-grid (V2G) functionalities for optimized energy flow. The model is evaluated using real distribution network data with seasonal load variations. The results reveal that with 10% EV penetration, hourly pricing can significantly reduce charging costs for EV owners (up to 28% and 31% during summer and winter, respectively). Additionally, it offers substantial relief for the grid by considerably reducing peak transformer load compared to flat or 2-part tariffs. This research demonstrates the potential of smart charging with dynamic pricing as a cost-effective and efficient solution for promoting EVs in Pakistan while mitigating grid congestion.

Keywords: Distribution Grid; Electric Vehicles Smart Charging; Energy Management; Machine learning; Optimization; V2G & G2V

CHAPTER 1: INTRODUCTION

1.1 Overview:

As the world evolves toward greater industrialization and improved living standards, the need for energy is rising. Oil, natural gas, and coal, which are all fossil fuels, encounter a substantial percentage of this energy need. Fossil fuel emissions that contribute to global warming harm the ecosystem. Fossil fuel consumption has negative effects, some of which include climate change, altered rainfall patterns, and unpredictable weather. Fossil fuels are heavily used in the transportation industry. The majority of the world's energy demand is accounted for by the transportation sector's reliance on fossil fuels. Due to continuously evolving environmental issues, there is a need to boost green technology.

Concerns about conventional cars and energy sources are currently being raised due to environmental and climate change issues [1]. The transportation sector is a significant contributor to pollution worldwide due to its role in increasing levels of fine particulate matter (PM2.5), ozone, and nitrogen dioxide [2]. This is what has sparked the electrification of transportation worldwide. As a result, researchers around the world are concentrating on using renewable energy sources (RES) to power the transportation sector.

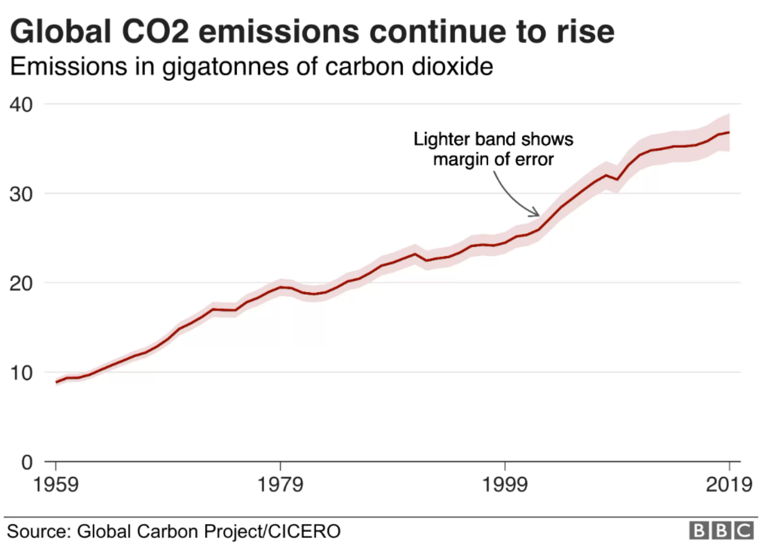


Figure 0.1: Increasing CO2 Emissions due to transport sector

The popularity of electric vehicles has grown due to environmental concerns regarding exhaust emissions and the insufficiency of petroleum resources. Electric vehicles provide promising solutions regarding environmental concerns [3]. However, the growing use of PEVs in distribution power networks is causing many difficulties, for instance, distribution transformer stress, undesirable peaks, congestion in transmission lines, voltage violations, and growing system losses [4]. Issues like the heavy cost and deterioration of electric vehicle batteries as well as the time needed for charging them should also be considered [5].

Uncoordinated charging of electric vehicles negatively impacts the grid such as deteriorating the system's voltage profile [6]. According to some researchers, up to 10% penetration of uncoordinated charging of EVs is acceptable, but more than that harms the system.

It is worth exploring the possibilities of using PEVs to provide auxiliary services to the distribution power grid in controlling active and reactive power [7]. A lot of researchers are working on various aspects of charging electric vehicles. Control of the charging of PEV batteries is essential for integrating PEVs into the distribution grid and minimizing the impacts of widespread PEV adoption. Vehicle-to-grid (V2G) and grid-to-vehicle (G2V) technologies were put up as mutually beneficial options for PEV owners and the grid operator. In G2V mode, extra electricity from the grid can be stored in the PEVs' batteries during off-peak hours. In the V2G mode of operation, PEVs can sell electricity back to the grid during the discharging phase [8]. Controlled EV charging has various potential benefits because charging can begin when electricity is inexpensive or when energy from other renewable sources is offered. Moreover, EVs can power resident loads connected to the distribution network. In this method, the congestion in the electric transmission network is reduced and EV owners can make money. However, the algorithms for charging and discharging EVs must consider the needs of EV users and the finite number of cycles for electric vehicle batteries [9].

1.2 Motivation:

On the transportation front, Bloomberg New Energy Finance predicts that electric vehicles will account for the majority (54 percent) of new car sales worldwide by 2040, and 33 percent of all light-duty vehicles on the road. The study's main finding is that the EV revolution will impact the car market considerably harder and faster than expected a year ago. It predicts that by 2040, EVs would account for 54% of all new light-duty vehicle sales worldwide as shown in Figure 0.2.

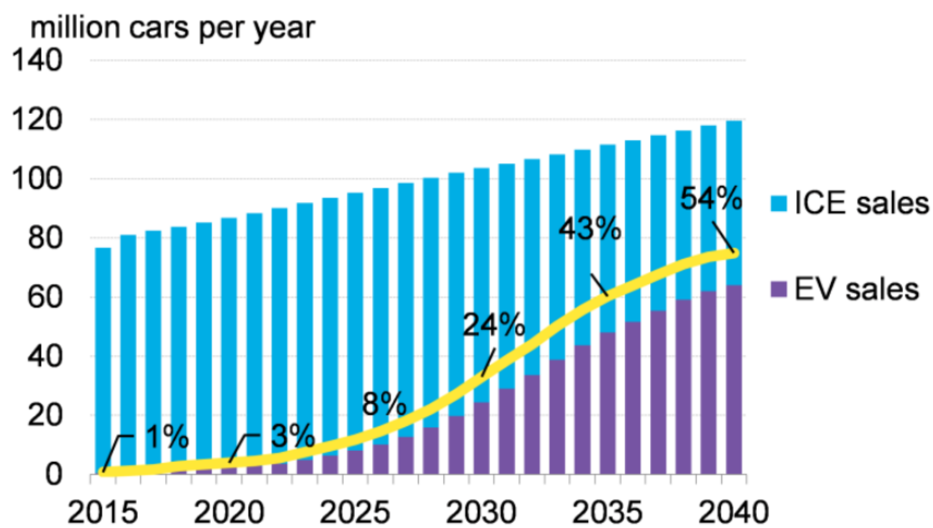


Figure 0.2: Electric vehicles sale is getting increased

Uncoordinated charging of electric vehicles negatively impacts the grid such as deteriorating the system's voltage profile [6]. According to some researchers, up to 10% penetration of uncoordinated charging of EVs is acceptable, but more than that harms the system. The main motivation behind this study is to develop coordinated charging for the electric vehicles that helps to reduce the negative impacts on the power system.

Since EV chargers are already widely used, it is important to highlight the risks and discuss potential fixes in order to prevent the power grid from failing. Since most EVs are plugged in at night, the load of EV charging in residential areas may increase during the nighttime electricity requirements. Commercial chargers with high power might introduce a new peak to the system load and violate important electrical distribution system characteristics, which is a severe issue. 10% and 20% penetration of electric vehicles can result in 17.9% and 35.8% increase in peak load for a typical distribution system respectively [10]. Power losses and voltage variations in the system are increased with higher peak load. Transformer and line heat limits may also be violated as a result [11].

As the penetration of EVs is increasing, the risks need to be pointed out along with possible solutions to avoid the failure of the power system. In residential areas, EV charging load may increase power requirement at night-time as most people plug EVs at night- time. To overcome the issues that result due to uncoordinated charging of electric vehicles, this study has proposed an energy management strategy.

1.3 Research Objectives:

The main objective of this study is to develop an energy management strategy for the electric vehicles in order to accommodate the increasing penetration of electric vehicles and to minimize the negative impacts of electric vehicles penetration on the power system in the developing countries like Pakistan. Another objective of this study is to mitigate the congestion in the distribution system that results due to the un-coordinated charging of electric vehicles. The primary goal of this research is to propose some cost-effective EV charging solutions to induce users to use electric vehicles.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction:

In this chapter, the literature review is presented. In section 2.2 different strategies have been highlighted for the controlled electric vehicles charging for energy management of electric vehicles. Different methodologies have been discussed in detail and their pros and cons have also been discussed. In section 2.3 novelty points of this research have been discussed.

2.2 Strategies for Energy Management of Electric Vehicles:

For energy management of electric vehicles, multiple approaches have been discussed in the literature. They are related to machine learning, mathematical modeling, heuristic, statistical, practical utility approaches, market-based strategies, and agent-based modelling.

2.2.1 Machine Learning Based Strategies:

A variety of machine learning-based strategies have been proposed. A study [12] developed a deep learning framework based on the harmony search algorithm for distribution automation system management that considered the social and technical costs of using renewable energy sources and electric vehicles. A study in [13] provides a three-stage deep learning-based system to develop the day-ahead optimal charging schedule for electric vehicles. Since the driving cycle significantly influences the performance of the energy management system, an adaptive wavelet transform-fuzzy logic control energy management strategy based on driving pattern recognition was proposed in [14]. Hybrid energy storage systems are composed of batteries and supercapacitors in electric vehicles. Fuzzy logic control was used to maintain the state of charge of the supercapacitor and the battery.

2.2.2 Mathematical Modelling:

Some researchers have adopted mathematical modeling to regulate the energy of electric vehicles. A mixed-integer linear programming model was proposed for intelligent energy management with a hybrid PV scheme [15]. It minimized energy consumption costs by optimizing residential appliances and Electric vehicle charging. The grey wolf optimization algorithm was proposed in [12] to solve mixed integer non-linear programming models. Peak shaving can be used to provide load balancing when using EVs as energy storage devices [16]. To overcome the uncoordinated charging problem and to avoid the peak load a study was performed for charging EVs during the off-peak time to fill the demand valley and clip the peak load by discharging EVs during peak hours [17].

2.2.3 Heuristic Approaches:

Heuristic and statistical approaches have also been reported in the literature. By considering load forecasting, co-optimization of load frequency control error and V2G was implemented by using the numerical properties of the active power network [18]. Integrated demand response was used to alleviate the congestion in the transmission and distribution network [19]. A heuristic supervisory rule-based energy management strategy was proposed in [20] to control loads of electric vehicles by using PV generators. The battery storage facility offers reduced costs for continuous daylight charging compared to direct charging through the grid. An energy management strategy was proposed for a large electric vehicle charging station by chance-constrained programming and Monte Carlo simulation [21]. To alleviate the congestion in the distribution system, the optimal location of charging spots was proposed in [22], after running the load flow analysis using Newton Raphson method.

2.2.4 Practical Utility Approaches:

Practical utility approaches have been explored for mitigating congestion. A study in [23] discusses the effects of increasing EV adoption and the possibility for higher demand on the distribution system, which demands load optimization to maintain sustainable development. A distribution Locational Marginal Price algorithm-based study found that including electric bus charging load in demand response helped alleviate the network congestion and reduce the power loss by 7.2% in the distribution network [24]. Using the day ahead framework, an optimization algorithm was proposed for the optimum charging of EVs by using the charging data from a real-world pilot program [25]. By using time-of-use pricing, optimal charging was scheduled by connecting reactive power-compensating devices in the system to maintain the voltage profile [26]. In [27], renewable energy resources and electric vehicles' battery storage were combined by considering the demand response approaches such as critical peak pricing (CPP), real-time pricing (RTP), and time of use (TOU). By analyzing results, it has been observed that real-time pricing gives more savings as compared to the other two pricing schemes.

2.2.5 Market Based Approaches:

Some researchers have discussed market-based approaches for the energy management of electric vehicles. An algorithm was proposed in [28] to prevent line congestion by motivating EV aggregators to actively participate in the market. The market-based strategy used the concept of network-constrained transactive energy to address the conflicts between TSO and DSO in congestion inhibition. A decentralized market framework strategy was proposed in [29] for the active contribution of market participants to alleviate the congestion in the system. EVs act as distributed generation sources along with other renewable energy sources. A decentralized framework was proposed for the active distribution network by considering the active participation of EV aggregators [30]. In [31], an algorithm was proposed by considering the EV aggregators, distributed generation, and market operators to alleviate the congestion in the distribution system. Researchers suggested a framework for deregulated market participation where participants using renewable energy sources are urged to assist the system to reduce congestion. To maintain system security, electric vehicles not only served as a load but also as a source of generation [32].

2.2.6 Agent Based Modelling:

Agent-based modeling has been discussed in reference [33] to handle the energy for EVs and EV charging stations (EVCSs). The system operator acted as the master decision maker while EVs and EVCSs worked as independent decision makers to handle their energy scenarios. EVs' and EVCSs wanted to maximize their financial profit while the system operator indirectly controlled their energy scenarios to maintain the system constraints. GAMS software was used to implement this optimization process. Multi-agent selfish collaborative architecture (MASCO) was proposed in [34]. A multi-agent multi-objective reinforcement learning architecture was designed to facilitate EV charging while reducing energy bills and preventing transformer overloads. MASCO was configured to the customer choices, worked under any form of tariff, and required very few assumptions about the distribution grid.

2.2.7 Pricing Strategies:

Many studies analyze the effect of EV charging on operating costs and grid conditions under different pricing regimes and propose various pricing strategies for effective management. Due to the growth of electric vehicles intricacy between electric power and transportation systems increases so enhancing their operational performance becomes vital. In [35] an electric vehicle charging station and an electric vehicle aggregator coordinate without exchanging or disclosing private information. The gameplay between two non-cooperative stakeholders is represented by a marginal price-based coordination model. The merits of the suggested model are demonstrated by a numerical analysis that shows an overall 78.3% drop in costs. In [33], a quarter-hourly dynamic pricing solution based on the deep deterministic policy gradient reinforcement learning algorithm is implemented to fully exploit EV scheduling potential by overcoming the discrete problem of the usual time-sharing pricing model for EVs. Using annual actual EV trip data from a specific region of North China and price data from the electric power trading market, three distinct pricing regimes are used to analyze scenarios of EV revenue and load variations.

Analysis in [36] particularly focused on the state of California to 10% of overall costs). By considering Time-of-use (TOU) prices for charging during night hours comparable cost savings are attained. The findings indicate that smart charging in combination with TOU rates with expanded daytime periods are the policies most likely to progress California's dual PEV and RE targets.

Multi-objective techno-economic-environmental optimization in [37] is used for planning out the charging and discharging of electric vehicles. In comparison to uncontrolled electric vehicle charging, the suggested strategy reduces energy costs, battery deterioration, CO2 emissions, and grid utilization by 88.2%, 67%, 34%, and 90%, respectively. Additionally, the system operator needs to pay the end-user of electricity and the owner of an electric vehicle to increase participation in energy services and improve grid utilization by 41.8%. Without modeling the distribution network, a techno-economic study for an aggregator-controlled electric vehicle charging station in Egypt is proposed in [38]. In the first stage, Mixed-integer linear programming (MILP) is used, and the peak demand value is reduced to 48.17% without using any additional battery storage devices. In the second stage, MILP and Markov Decision Process Reinforcement Learning (MDP-RL) increased EVCS revenue by 28.88% and 20.10%, respectively.

2.3 Novelty Points of this Research:

Despite extensive research on energy management of electric vehicles and congestion management of the power system, no work reported using a real distribution network model and proposing any new type of Hourly Price that can help to enhance the use of electric vehicles while coping with the energy crisis in developing countries such as Pakistan. The proposed strategy has the following properties that distinguish it from the existing literature:

- A real distribution feeder network of LESCO populated with real load profile data of typical houses in Lahore is modeled for meaningful impact analysis of EV penetration in developing countries like Pakistan.
- A real dataset for conventional vehicles in Pakistan is updated for electric vehicles and used to accurately predict SOC for EVs. Different machine-learning models are explored for SOC prediction accuracy and a gradient-boosting regression algorithm renders the most accurate results.
- In the absence of wholesale/retail real-time market pricing, a new method is proposed for discovering hourly variable retail pricing for Pakistan, by considering the feeder's load profile.

- K-means clustering is performed to analyze the feeder condition.
- Modeling and simulation are done in Jupyter Notebook by using Pandapower libraries. It is an open-source Python-based tool that can achieve quicker load flow solutions than other power systems tools. Agent-based modeling has been employed to mimic private data and decision-making by EV owners, EV aggregators, and utility operators.

CHAPTER 3: METHODOLOGY

3.1 Introduction:

The proposed work is about the energy management of electric vehicles at the minimum cost and congestion management of the power system. The methodology adopted for conducting the proposed research work is explained in the following six steps.

3.1.1 State of Charge Calculations: (EV Load Estimation)

The cubic capacity of the engine in a conventional vehicle is measured in centimeter cubes (cc). Therefore, the vehicles dataset published in [39] contains cc ratings of the vehicles. For this research, using the information on electric vehicle batteries in [40], the cc of vehicles is converted into the battery capacity for electric vehicles. Electric vehicles' load on the feeder depends on the final state of charge of vehicles upon reaching back home. However, since the dataset [30] is for conventional vehicles, it lacks data on the final state of charge of electric vehicles. Therefore, calculations for the final state of charge of the electric vehicles are carried out by using the following formula proposed in [41].

$$\mathrm{SOC_{final}} = \mathrm{SOC_{initial}} - \frac{\mathrm{du}}{\mathrm{c}} * 100 \tag{3.1}$$

where d indicates the distance traveled by the vehicles, u represents the specific energy consumption in kWh/km and c is the capacity of the battery in kWh. $\mathrm{SOC_{initial}}$ and $\mathrm{SOC_{final}}$ are the states of charge of the battery at the start and end of the day, respectively. $\mathrm{C_{initial}}$ is randomly initialized for all the electric vehicles. Electric vehicles that are connected to the feeder have a battery capacity in the range of 15 kWh to 20 kWh. The charging and discharging rate of electric vehicles is considered 1.9 kW according to the specification of level-I chargers [42]. Since we are proposing a solution for a typical residential feeder, EVs returning home in the evening need overnight charging to be ready for the next day. Therefore, the final state of charge is required as input for the proposed algorithm to devise the least cost overnight charging schedule according to the requirements of the EV owners.

The updated electric vehicles dataset is utilized for training the machine learning algorithms to predict the final SOC.

3.1.2 State of Charge Estimation by Machine Learning Algorithms:

To design the charging schedule for the electric vehicles, the first step is to identify the state of charge of the electric vehicles. The final state of charge of electric vehicles is predicted by using the initial parameters of different electric vehicles. Multiple ML algorithms including random forest regression, XGBoost regressor, CatBoost regression, and gradient boosting regression tree, have been used to predict the accurate SOC.

The random forest regression algorithm is bootstrapping the data by choosing subsamples randomly for every iteration of building trees. XGBoost regressor combines the best features of AdaBoost and random forest. By adding some additional features such as minimizing the loss function using gradient descent, this algorithm performs better as compared to AdaBoost and random forest [43]. CatBoost expands on gradient boosting and decision tree theory. The basic goal of boosting is to successfully combine many weak models that just slightly outperform to produce a strong and competitive predictive model through greedy search [44].

Ensemble-based algorithms are becoming popular for their ability to solve prediction and classification problems. The tree-based ensemble method intentionally combines various simple tree models to improve predictive performance rather than fitting the one best model. Additionally, the tree-based ensemble method can fit complex nonlinear relationships, requires minimum data preparation, and handles numerous predictor variables. Gradient boosting algorithms have great significance in predicting travel time [45].

Different parameters affect the performance of the gradient-boosting algorithm such as the depth of the tree and the number of estimators. Assume that J leaves are present on each tree. Each tree divides the input into J disjoint regions R_{1m}, R_{2m}, ……, R_{Jm} and forecasts a constant value b_{Jm} for region R_{Jm}. Regression tree can be mathematically written as [44]:

$$g_{m(x)} = \sum_{J=1}^{J} b_{Jm} I(x \in R_{Jm} \tag{3.2}$$

These algorithms are trained and tested on a dataset used in [45]. The dataset, comprising of 187 various kinds of vehicles, contains information regarding the distance travelled by vehicles in km, their departure time, arrival time, and battery capacity. The dataset is divided into training and testing datasets by using Scikitikit learn library in Jupyter Notebook. Training and testing datasets are considered 70% and 30%, respectively, of the complete dataset. By using GridSearchCV, initial parameters for the different algorithms have been tuned.

3.1.3 Battery Degradation Costing:

Battery degradation cost is the main consideration for EV owners while considering V2G mode. During the V2G mode, EV owners supply the power to the grid at a price higher than the charging price because it is economically beneficial. However, rapid charging and discharging reduces the battery life thus there is a need to replace the battery more frequently. In this study, the degradation cost of a lithium-ion battery is modeled because it is a popular choice for an EV due to its relatively higher energy density, greater efficiency, and longer life. The cost of battery degradation is formulated as a function of battery power and depth of discharge during a specific time interval [47], as shown below:

$$C_b^d(t) = \frac{C_b * P_b(t) * \Delta(t)}{EV_{b_{cap}} * I_c\big(DOD_b(t)\big) * \eta} \tag{3.3}$$

$$I_c\big(DOD_b(t)\big) = 694 * \big(DODd_b(t)\big)^{-0.795} \tag{3.4}$$

$$DOD_b(t) = 1 - \frac{EV_b(t)}{EV_{b_{cap}}} \tag{3.5}$$

Where $C_b^d(t)$ is the battery degradation cost at time t in \$, C_b is the capital cost of the battery (\$), $P_b(t)$ is the amount of power discharged by battery at time t, $\Delta(t)$ is the time interval taken as 1 hour in this study, $EV_{b_{cap}}$ represents the electric vehicle battery capacity and $EV_b(t)$ battery SOC at time t, $DOD_b(t)$ is the battery depth of discharge status at time t, $I_c\big(DOD_b(t)\big)$ is the number of cycles of battery storage, and η is efficiency of the battery.

3.1.4 Real Feeder with Synthesized Load:

Security and privacy policies regulating critical infrastructure data can restrict researchers from accessing data of real power systems, but data access is essential for technical development [48]. A small number of standardized networks, such as the IEEE transmission and distribution test cases, have been widely utilized by academics for decades. More recently, researchers have tried to generate synthetic distribution systems but studies involving real distribution system data are not common.

A model of the Gulshan-e-Iqbal distribution feeder of LESCO is used for this research work. All system parameters such as conductor specifications, buses, and transformers are similar as reported in [49]. However, the load of the feeder is synthesized from data of typical summer and winter load profiles of Pakistan reported in the State of Industry Report published by NEPRA in 2019.

LESCO has provided the load data for the Gulshan-Iqbal feeder only for the peak hours that are utilized in [42] and [50]. Using typical summer and winter season load variations in Pakistan, 24-hourly load curves shown in Figure 0.1 are constructed for the

Gulshan-e-Iqbal feeder for summer and winter season. It is observed that during summer season peak demand occurs at 01.00 and during winter season peak demand occurs at 19.00.

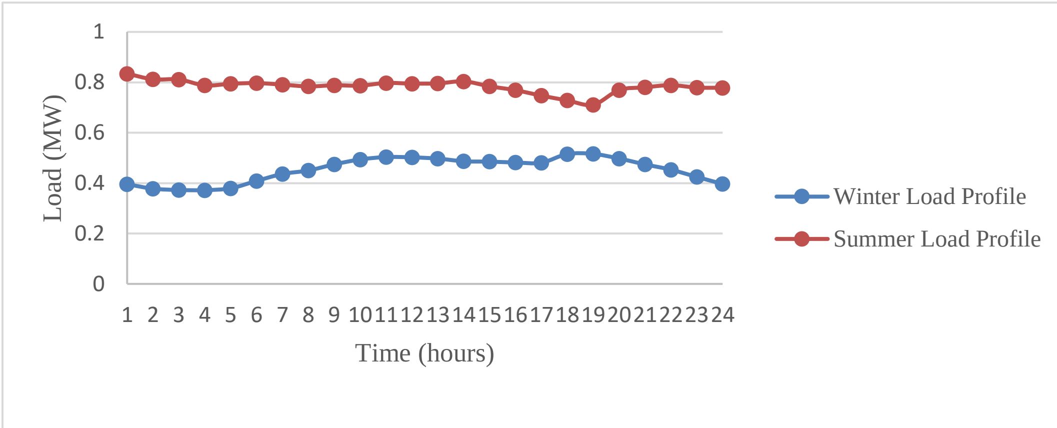


Figure 0.1: Load profile of Gulshan-e-Iqbal feeder

3.1.5 Proposed Price:

In Pakistan, DISCOs offer a Flat Rate to most residential customers connected by single-phase meters and a 2-part Tariff to the minority provided by three-phase meters. Prices considered in this research are 37.8 Rs/kWh as the Flat Rate whereas 35.57 Rs/kWh and 41.89 Rs/kWh as the 2-part Tariff of LESCO for off-peak time and on-peak time, respectively as reported on the LESCO website. However, since hourly variable pricing signals do not currently exist, optimal power flow is run on a reduced 114-bus network of the national grid to find a new Hourly Price for this research. The resulting Hourly Price curves for the summer and winter seasons are shown in Figure 0.2 and Figure 0.3 respectively.

Figure 0.2 shows that during summer season for Hourly Price case, price is highest at 01.00 hour and for 2-part tariff case peak hours are from 19.00 to 23.00. Figure 0.3 indicates a new trend for Hourly Price case during winter season, as maximum price is on 19.00 hour and for 2-part case, peak hours are from 17.00 to 21.00. Flat rate remains same for both seasons.

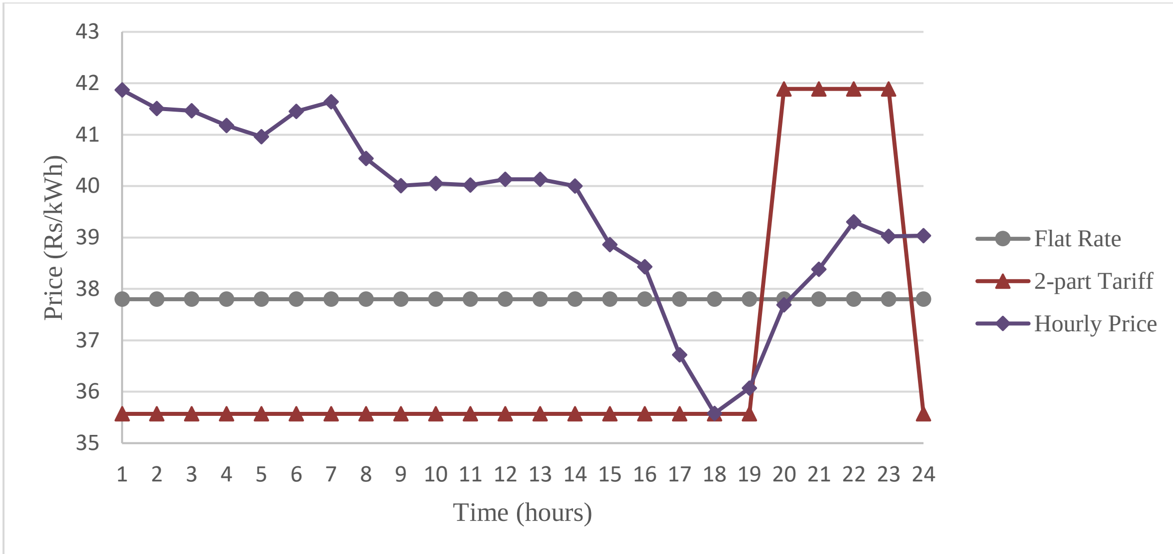


Figure 0.2: Price during summer season

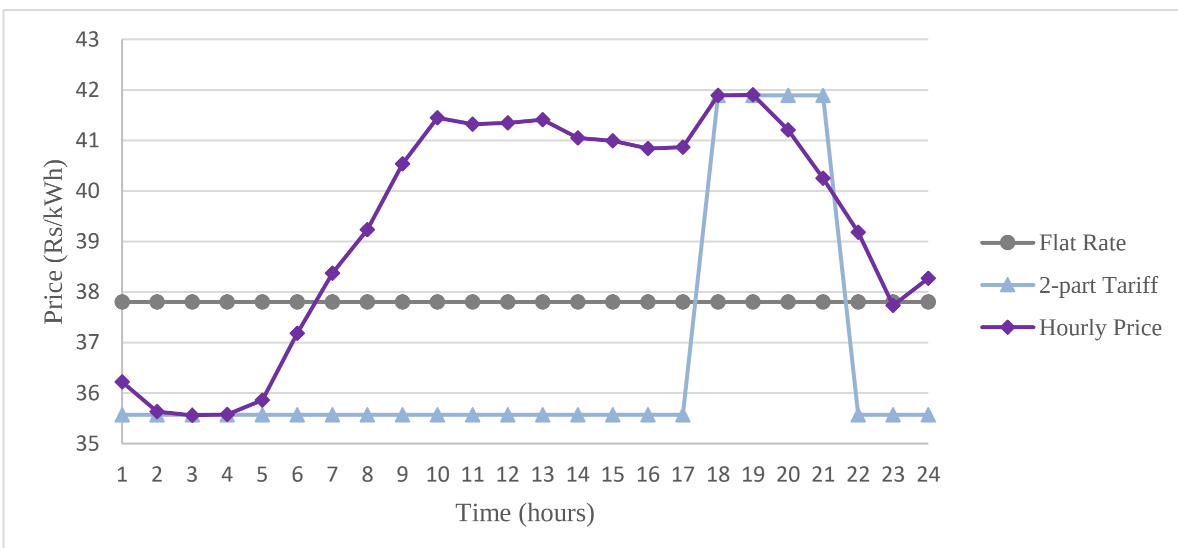


Figure 0.3: Price during winter season

3.1.6 Agent-based Modelling:

The proposed work for the energy management of electric vehicles to mitigate the congestion of the power system is tested over the 11KV feeder of Gulshan-e-Iqbal LESCO. The feeder has 60 transformers of different KVA ratings. This work relies on programming in Python by using Anaconda Jupyter Notebook, whereas the feeder is designed by using Pandapower libraries. Load flow studies have been performed by using the Newton-Raphson algorithm. The planning departments of all Discos in Pakistan use synergy software. After extracting the .kmz file of the Gulshan-e-Iqbal feeder from the synergy software, it was loaded into Google Earth to visualize the route of the feeder. Figure 0.4 shows the resulting street layout of the Gulshan-e-Iqbal feeder on a Google map. The feeder, managed by a utility operator, is divided into six zones as shown in Figure 0.4**,** each managed by an EV aggregator. The maximum load on the feeder is 0.8624 MW. The formula used to calculate the number of EVs is given below:

$$\mathrm{EV_{Load}} = \text{\%age EV Penetration} * \text{Maximum Load on the Feeder} \qquad (3.6)$$

$$\text{Total EVs} = \text{round}\left(\frac{\text{EV Load}}{1.9\text{KW}}\right) \qquad (3.7)$$

From the equation (3.7), for 5% and 10% penetrations, 23 and 46 electric vehicles have been considered, respectively. The number of electric vehicles for each zone is selected based on the number of nodes in each zone and placed randomly. Electric vehicles connected in each zone convey their information to their relevant aggregator, and the utility operator provides information related to the loading of transformers and the tariff to all six EV aggregators. When the utility operator conveys the information regarding the loading conditions and the tariff to the EV aggregator, it has the private information of all the EVs that are connected in its zone. Therefore, the EV aggregator develops the optimal charging schedule for its electric vehicles with the objectives of mitigating the high loading conditions and charging the vehicles at the least cost.

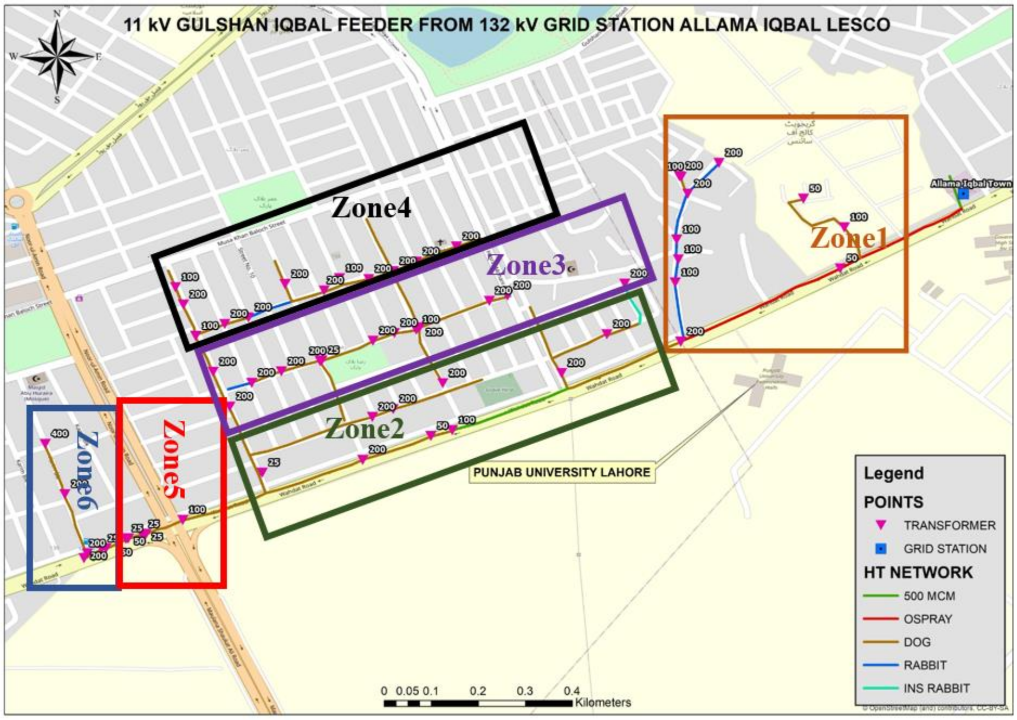


Figure 0.4: 6 Zones in Gulshan-e-Iqbal Feeder

CHAPTER 4: CASE STUDIES

4.1 Introduction:

Three case studies have been explored in this work namely Flat Rate, 2-part Tariff, and Hourly Price. Since it is a residential feeder, it is assumed that all the electric vehicle owners come back home between 4 p.m. and 9 pm. The number of electric vehicles returning home for each hour is formulated by using the MATLAB curve fitting tool and it is given by the equation (4.1).

$$\mathrm{EV}(x) = \frac{1}{1.668\sqrt{2\pi}}\ \exp^{-0.5\left(\left(\frac{x-18.5}{1.668}\right)^{2}\right)} \tag{4.1}$$

here $\mathrm{EV}(x)$ indicates the probability density function (PDF) for the electric vehicles returning home in an hour x. For this Gaussian PDF, mean is 18.5 and the standard deviation is 1.668.

4.2 Flat Rate:

Figure 0.1 shows that in case of Flat Rate, the EV owners connect their vehicles as soon as they come back home. Due to the Flat Rate, they do not consider loading conditions or the peak time of the load. Therefore, the system may experience heavy loading and consequently congestion in the power system.

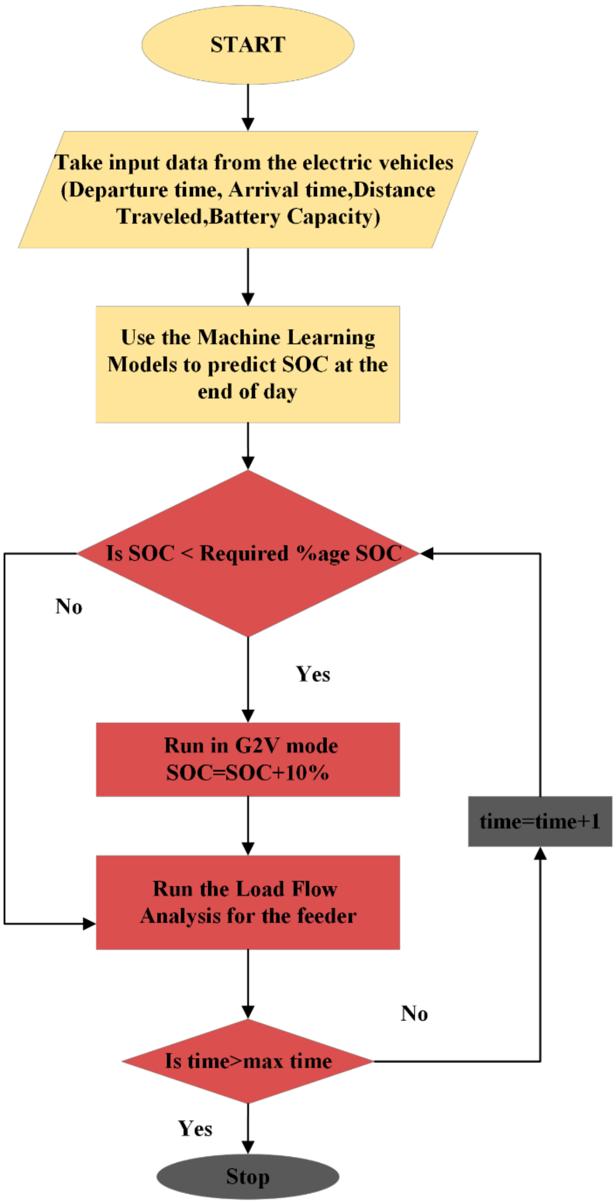


Figure 0.1: Flow chart for Flat Rate

4.3 Two-Part Tariff:

In the second case of the 2-part Tariff, the price of electricity is high from 6 pm to 11 pm as noted in [51]. Consequently, vehicle owners do not charge their vehicles right away upon returning home, as shown in Figure 0.2. Instead, vehicle owners with adequate SOC communicate with their aggregator upon reaching home. In the meantime, aggregators get the status of network conditions from the utility side. Therefore, the aggregator has information on both network conditions and SOC of EVs. If transformers are loaded above 80% and EV owners have charged their vehicles at a low price, e.g. from solar PV in the afternoon to discharge at a higher evening peak price, then the aggregator will communicate to the utility operator and discharge batteries of vehicles in V2G mode. Meanwhile, voltage improvement by mitigating feeder overloading is beneficial for the utility and customers alike.

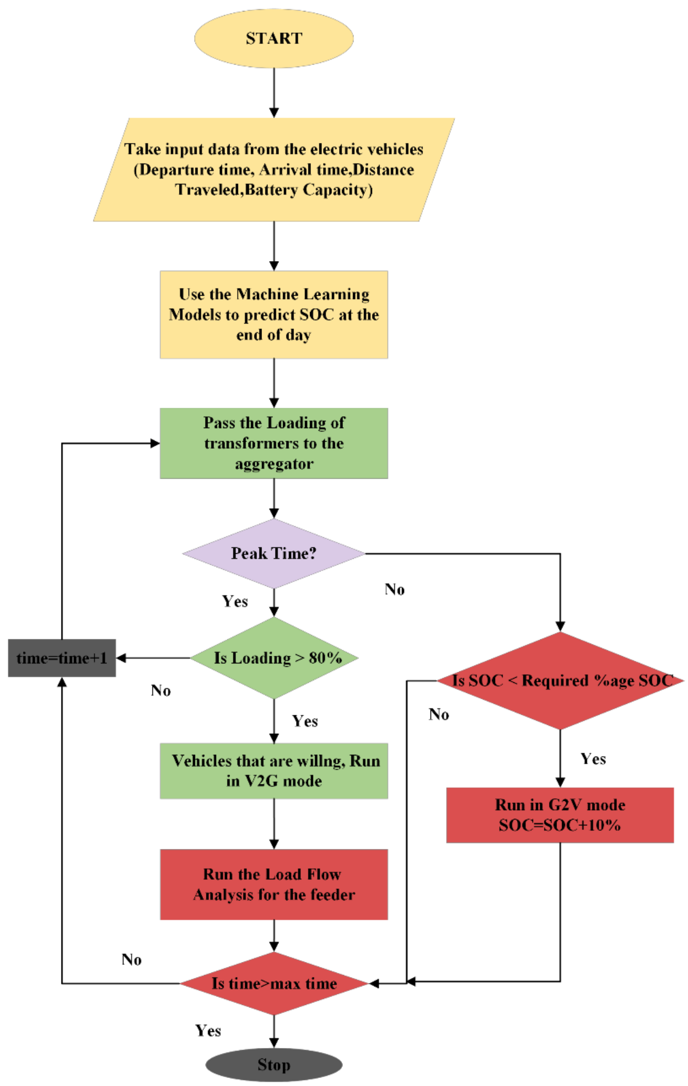


Figure 0.2: Flow chart for 2-part Tariff

4.4 Hourly Price:

In the last case, an Hourly Price is proposed for energy management by using both V2G and G2V modes, as shown in Figure 0.3. In this case, when the EV owners come back home, they inform their aggregator about their charging requirement for the next day. Since all the vehicles don't have to achieve 100% charging, all the vehicles are charged according to their next-day requirements. The algorithm finds out the least cost hours according to the charging requirement of EVs. This enables EV aggregators to develop charging schedules for their EVs to achieve the least-cost operation.

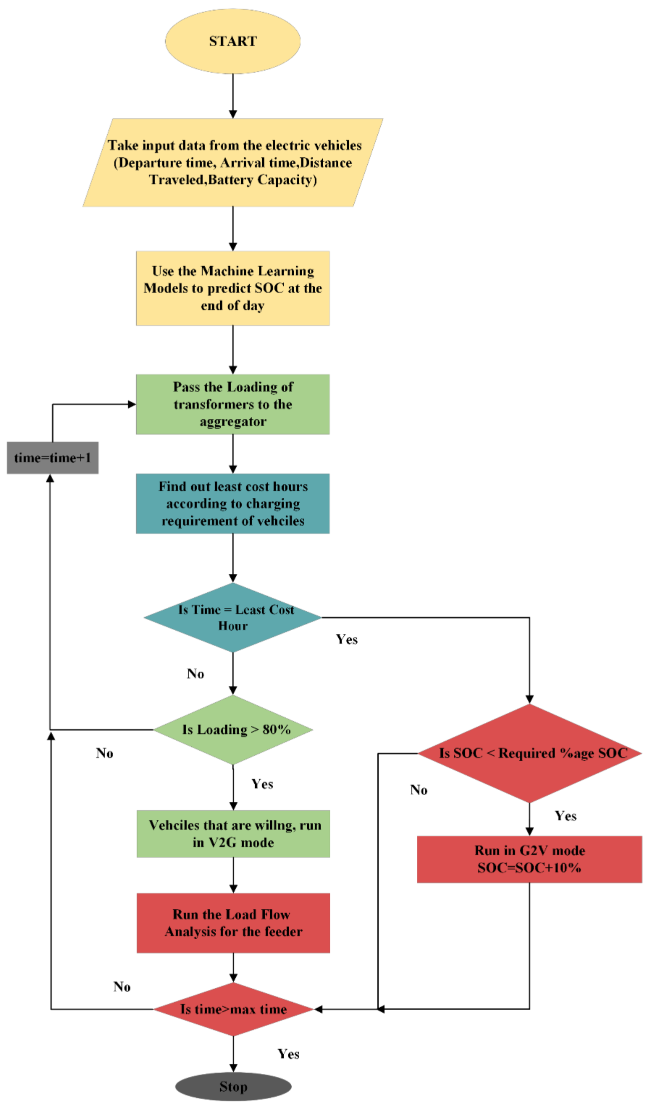


Figure 0.3: Flowchart for Hourly Price

1. CHAPTER 5: RESULTS AND DISCUSSION

The results of our research are presented and discussed as follows:

5.1 State of Charge Estimation by Machine Learning:

The state of charge at the end of the day is predicted by using multiple machine learning algorithms for comparison. Four machine-learning regression algorithms were tested to determine the final state of charge of different electric vehicles. Results for the final predicted SOC vs. actual SOC are presented in Figure 1.1. The results illustrate that the random forest algorithm has the least accuracy because predicted SOC values are lying away from the actual SOC line, as shown in Figure 1.1 (d). In comparison, Figure 1.1 (a) illustrates that the most accurate SOC predictions have been achieved by the gradient-boosting regression algorithm. Note that the results of the other two algorithms, depicted in Figure 1.1 (b), and (c) show intermediate accuracy as compared to the random forest and gradient boosting algorithms.

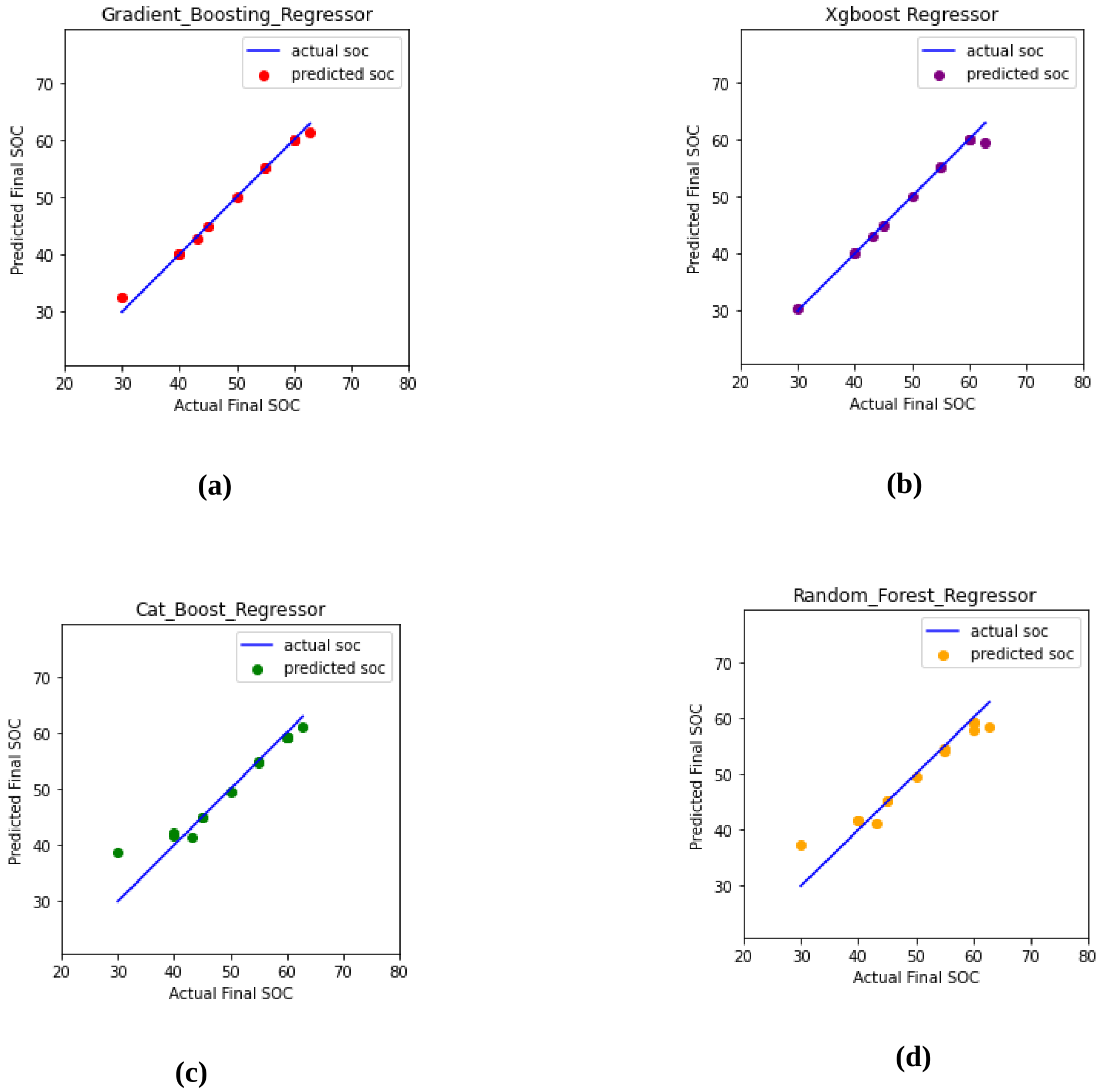


Figure 1.1: Machine Learning Algorithms (a) Gradient boost (b) Xgboost (c) Cat boost (d) Random Forest

The four algorithms have been compared based on the following three parameters; mean absolute error, mean squared error, and R^2 value. The comparative results of these parameters are listed in Table 1.1. R^2 value of 1 indicates the ideal case where all the predicted values are equal to the actual values. Gradient boosting regressor showed the best prediction results for this study because its R^2 value is 0.99, the mean squared error percentage is 0.0069 and the mean absolute error percentage is 0.0083. The worst results were delivered by the random forest regression tree algorithm with R^2 value of 0.93, the mean squared error percentage of 0.017 and the mean absolute error percentage of 0.065. In this research, gradient boosting algorithm has more accurately predicted SOC, as compared to its earlier reported applications in [23] and [52]. R^2 values obtained in [23] and [52] are 0.94 and 0.97, respectively, whereas in this study R^2 =0.99 has been achieved.

Table 1.1: Comparison of SOC Estimation Results by Different Machine learning Algorithms

Algorithm name	Mean Absolute error percentage	Mean squared error percentage	R^2 Value
Random Forest Regressor	0.017	0.065	0.93
Cat Boost Regressor	0.015	0.066	0.93
XG boost Regressor	0.0027	0.0082	0.98
Gradient boosting Regressor	0.0083	0.0069	0.99

In applied machine learning, cross-validation is generally used to estimate the skill of a machine learning model on unseen data. That is, to use a small sample to assess how the model will perform in general when used to generate predictions on data that was not utilized during the model's training. The process has a single parameter called k that specifies the number of groups into which a given data sample should be divided. As a result, the process is frequently referred to as k-fold cross-validation. When a specific value for k is chosen, it may be substituted for k in the model's reference, such as k=10 for 10-fold cross-validation. In this research by using multiple values of k=2, k=3 and k=5 results have been observed. By using different values of k, it has been observed that there is no overfitting in the described results.

5.2 Variation in Transformer Loading under Alternative Pricing Regimes:

The transformer loading condition of the Gulshan-e-Iqbal feeder with different penetrations of electric Vehicles has been analyzed. During the summer season from base case results, when no electric vehicles were connected to the system, three nodes (21, 27, and 32) were observed as weak nodes. During the winter season, the base load is less as compared to the summer season. In the winter season only two nodes (21 and 27) have been identified as weak nodes, their loading increases by 80% during some hours when electric vehicles are connected to the system.

The detailed loading conditions for three selected nodes are presented here for brevity. For the rest of the system, K-means clustering indicated three clusters representing the whole feeder condition. The number of nodes in each cluster for the summer and winter seasons is presented in Table 1.2.

Cluster 1 for the summer season in Table 1.2 indicates the nodes whose loading is less than 10%. Cluster 2 indicates those nodes whose loading lies between 30% to 40% and Cluster 3 indicates those nodes whose loading is beyond 50%. Table 1.2 indicates there are 9 nodes in the feeder whose loading increases beyond 50% during the summer season.

During the winter season, Cluster 1 in Table 1.2 indicates the nodes whose loading is less than 10%. Cluster 2 indicates those nodes whose loading lies between 20% to 30% and Cluster 3 indicates those nodes whose loading is beyond 40%. It is observed that most of the nodes in the winter season are lightly loaded. There are 5 nodes in the feeder whose loading increases beyond 40% however during the summer season there are a greater number of nodes whose loading get beyond 50%.

Table 1.2: Clusters Data for Transformer Loading During Summer and Winter Season

Cluster	Number of Nodes During Summer Season	Transformer Loading Condition During Winter Season	Number of Nodes During Winter Season	Transformer Loading Condition During Winter Season
1	44	Less than 10%	45	Less than 10%
2	7	Between 30% and 40%	10	Between 20% and 30%
3	9	More than 50%	5	Between 40% and 50%

5.2.1 5% and 10% EV Penetration:

By using the predicted state of charge, EVs' charging schedule is designed for 2-part Tariff and Hourly Price. Electric vehicles were randomly connected at different nodes, out of the 60 load nodes. Then nodes 21, 27, and 32 were identified as three weak nodes of the feeder. As shown in Figure 0.4, Node 21 lies in zone 2 and the rating of its transformer is 25kVA. Node 27 is present in zone 3 and the rating of the transformer connected there is also 25kVA. Moreover, a 25kVA transformer is connected at node 32 in zone 5. By connecting electric vehicles over these nodes, transformer loading gets very high as they are already heavily loaded even in the base case.

Since it is reported in [42] that there is no congestion in the distribution lines of this feeder, the focus of this work is on the management of charging and discharging the electric vehicles in the distribution feeder while considering the congestion of the distribution transformers.

Figure 1.2 depicts the transformer loading results of node 21 for all three case studies. This node is selected because it is heavily loaded even in the base case when no electric vehicle is connected. Transformers that are operating within prescribed limits of 80% loading are indicated by green color. Yellow color depicts transformers that operate between 80% to 100%. Red color indicates the transformers when they start operating beyond 100% of operational limits. In Figure 1.2 (a), for the Flat Rate, the 0.8 p.u. threshold limit of the transformer is violated because vehicle owners have no incentive to change their charging patterns. In case of 2-part Tariff, transformer loading clearly dropped within limits between 19.00 to 23.00. EV owners with sufficient state of charge will discharge to get a high energy price and as a result transformer loading will drop within the limits. When the price of electricity varies hourly, EV aggregator decides whether to charge or discharge for each hour. EV owner returned home in the evening and their vehicles start charging as price of electricity during these hours are low as observed in Figure 1.2 (a). During late night hours from 1 a.m. to 7 a.m. price of electricity is high, Consumers can discharge their vehicles to mitigate congestion as it is observed from the Hourly Price bars in Figure 1.2 (a). During daytime hours from 8 a.m. to 4 p.m., EVs are not available at home so, during these hours power transformers are violating the limits even in the Hourly Price case as shown in Figure 1.2 (a). One major difference in the 5% and 10% penetration results is that violation of limits gets increased. The height of the red bars in Figure 1.2 (b) indicates greater limit violations for the 10% penetration. As depicted in Figure 1.2 (b) this transformer gets severely affected by 10% EV penetration. Since the rating of this transformer is just 25KVA, it is essential to upgrade this transformer for catering the anticipated load of EVs.

Figure 1.2 (c) illustrates the transformer loading for 5% EV penetration during the winter season. During some hours, when EV owner returns home transformer loading is greater than 80% in case of Flat rate and 2-part tariff as it is the peak loading time, when EVs get connected to the system during these hours transformer loading increases, however for the hourly price case during peak loading hours, transformer loading remains less than 80% even for the 10% EV penetration as depicted in Figure 1.2 (d). Major difference is observed during the summer and the winter charging pattern in case of 2-part tariff, as peak hours are different in both cases. For the summer season in the 2-part tariff case peak hours are from 19.00 to 23.00, and loading decreases as shown in Figure 1.2 (a) and (b), during the winter season peak hours are from 17.00 to 21.00 as shown in Figure 1.2 (c) and (d).

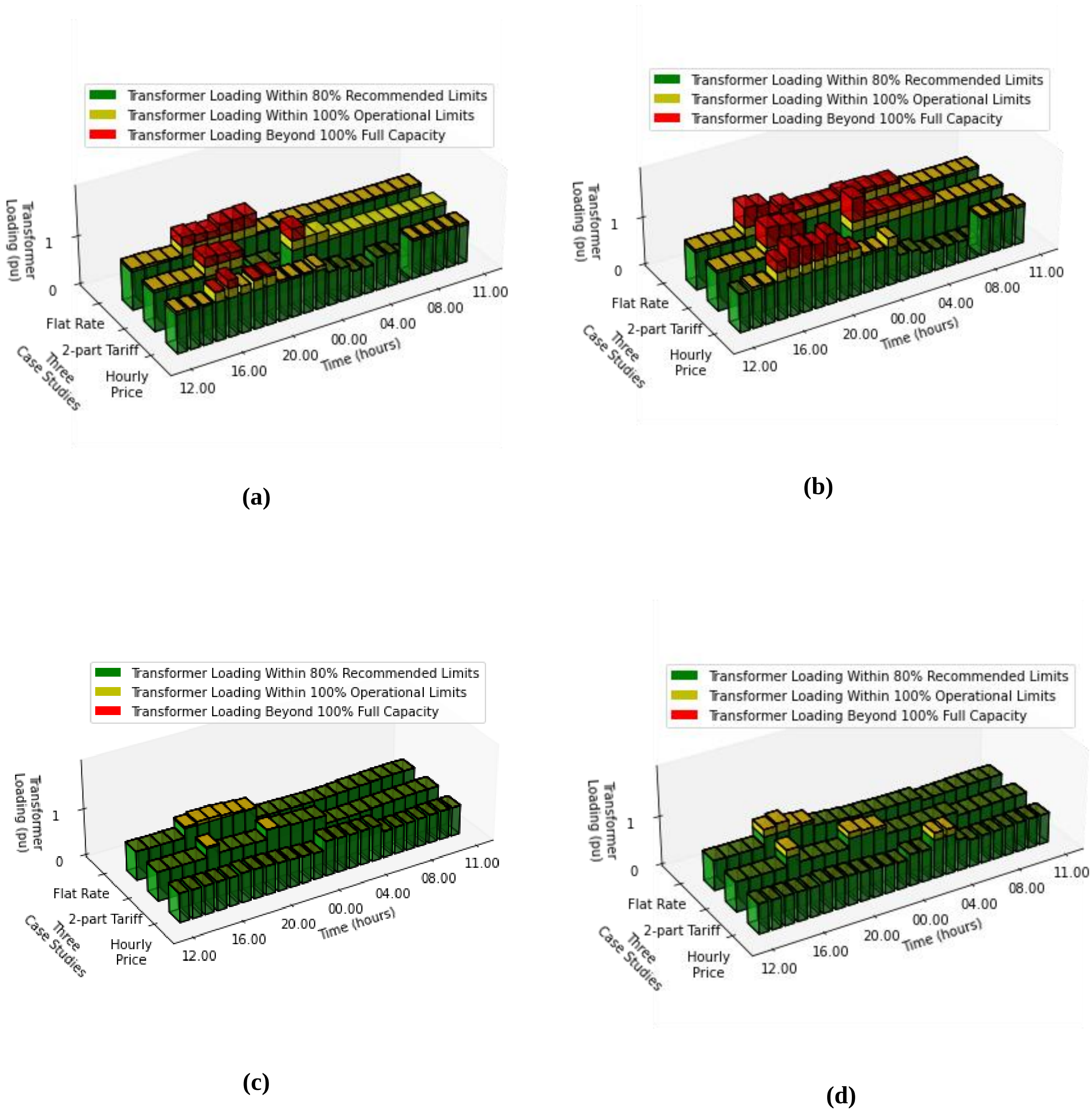


Figure 1.2: Transformer loading percentage at node 21 (a) 5% EV penetration during summer (b) 10% EV penetration during summer (c) 5% EV penetration during winter (d) 10% EV penetration during winter

In Figure 1.3 node 27 results have been presented. It shows that this node has a better condition as compared to the previous node. The limits that are violated in the Flat Rate and 2-part Tariff are greater as compared to the Hourly Price case, it depicted from the height of red bars in Figure 1.3 (a). For Flat Rate, transformer loading is getting increased from 16.00 to 21.00. For the 2-part Tariff case, loading behavior is different from the Flat Rate, as transformer loading increases from 16.00 to 19.00, and then on-peak hours start and vehicles are discharged to overcome the congestion or get the financial benefit of high price in those hours. From 23.00 onwards again vehicles get charged. For 10% penetration as shown in Figure 1.3 (b) violation of limits gets increased as more numbers of electric vehicles are getting connected. Figure 1.3 (c) and (d) shows the transformer loading condition during the winter season. Similar behavior has been observed as of the previous node for Flat rate and 2-part tariff. For hourly price case loading increases during late night hours as prices get reduced during that time.

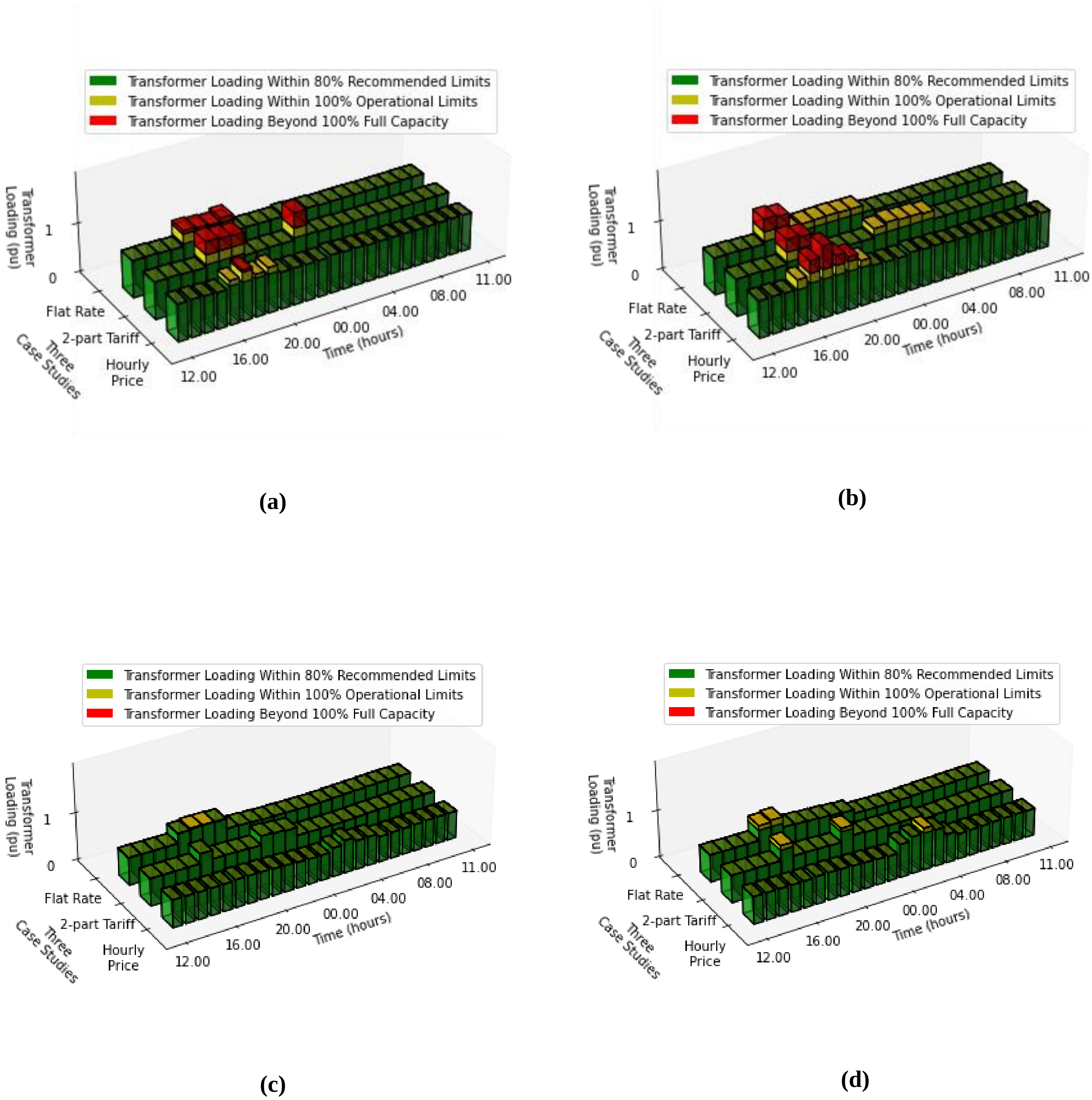


Figure 1.3: Transformer loading percentage at node 27 (a) 5% EV penetration during summer (b) 10% EV penetration during summer (c) 5% EV penetration during winter (d) 10% EV penetration during winter.

Figure 1.4 shows the results of all three case studies for node 32. Figure 1.4 (a) indicates transformer loading limits are violated for Flat Rate when EV started charging after returning home height of yellow bars increased. For the 2-part Tariff, four hours from 19.00 to 23.00. Rate of electricity is high, people discharge their vehicles and transformer loading decreases and EVs are charged from 12.00 to onward until they get the required percentage of charging, yellow bars indicating that transformer loading exceeds the recommended limits. For the Hourly Price, it is observed that during peak loading hours, loadings get lowered since the price is high in those hours, EVs owners get ready to discharge. In Figure 1.4 (b) Hourly Price case indicates that during V2G mode transformers, loading is exceptionally lowered, in those hours' the transformer load is about less than half because in 10% penetration number of vehicles increased larger vehicles discharged, consequently the loading of transformers decreased. Figure 1.4 (c) and (d) indicate the transformer loading during the winter season. It depicts that the transformer is operating within safe limits even for the 10% EV penetration.

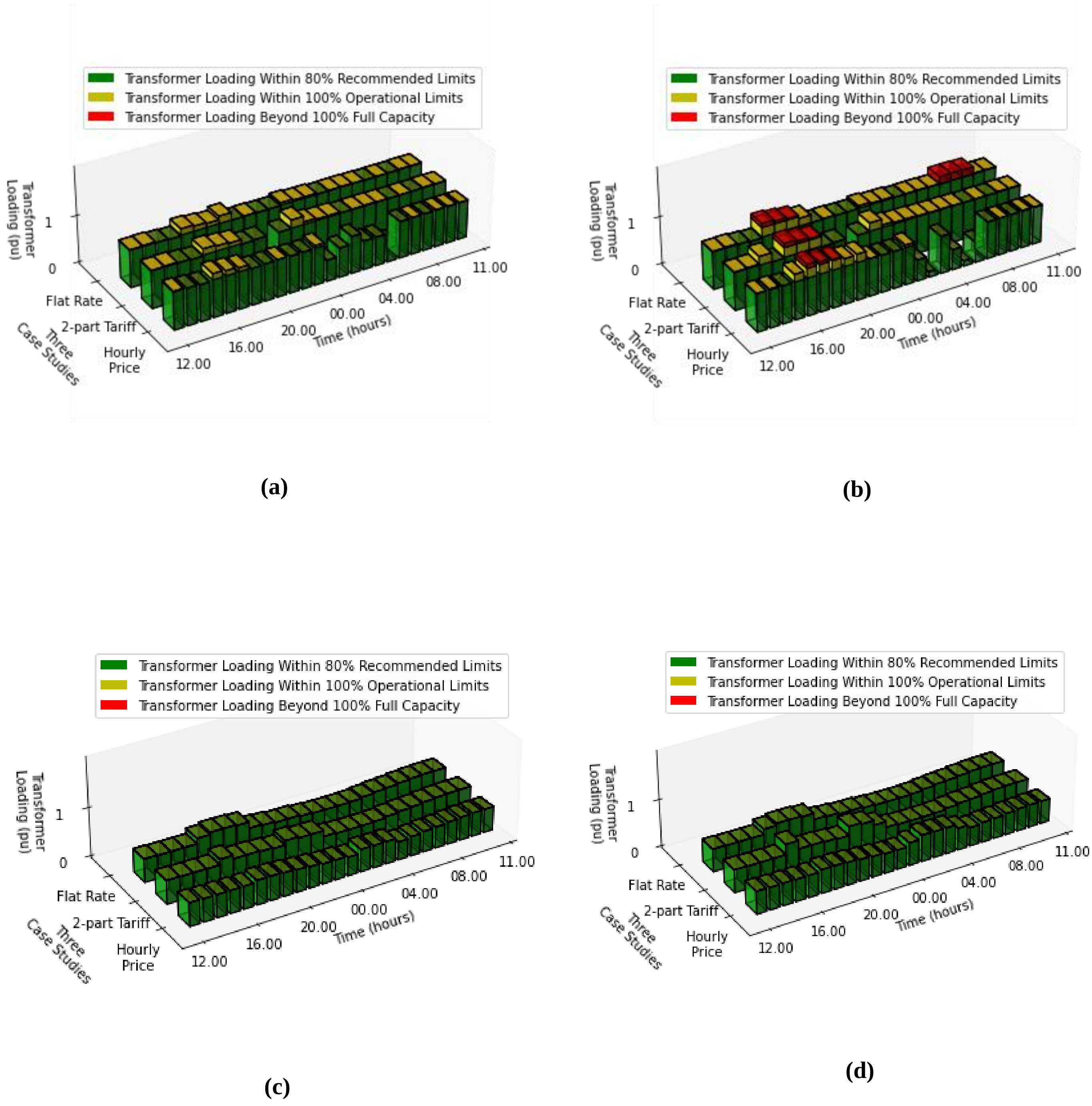


Figure 1.4: Transformer loading percentage at node 32 (a) 5% EV penetration during summer season (b) 10% EV penetration during summer season. (a) 5% EV penetration during the winter season (b) 10% EV penetration during the winter season

5.3 Voltage Profile of Feeder:

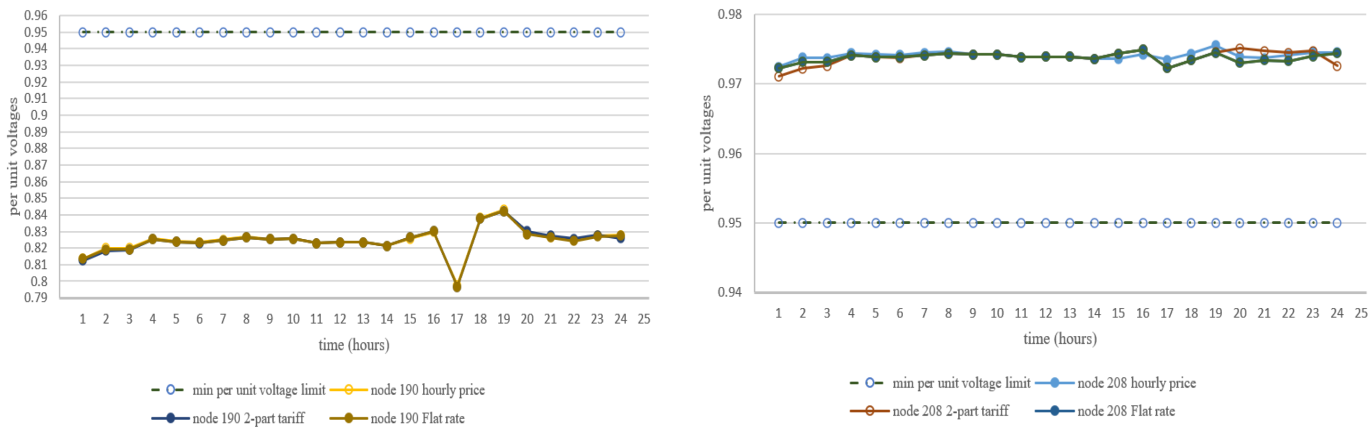
Since there are 301 nodes in the Gulshan-e-Iqbal feeder, it is not feasible to represent the voltage condition of every node. By using K-means clustering, it has been identified three clusters adequately represent the variety of voltage conditions in feeder. In Table 1.3 Cluster 1 indicates the nodes whose per unit voltages are in the range of 0.97 p.u to 0.98 p.u. Cluster 2 indicates the nodes whose per unit voltages are violating under-voltage limit of 0.95 p.u. Cluster 3 indicates the nodes whose per unit voltages are above 1 p.u but not greater than upper-voltage limit of 1.05 p.u.

During winter season, again by using K-means clustering, it has been identified there are three clusters would be enough to represent the condition of feeder. During winter season Cluster 1 in Table 1.3 indicates the nodes whose per unit voltages are in the range of 0.98 p.u to 0.99 p.u. Cluster 2 indicates the nodes whose per unit voltages are violating under-voltage limit of 0.95 p.u. Cluster 3 indicates the nodes whose per unit voltages are above 1 p.u but not greater than upper-voltage limit of 1.05 p.u. It is observed that most of the nodes in the winter season are within safe voltage operating limits. Only 25 nodes are violating the under-voltage limit.

Table 1.3: Clusters Data for per-unit voltage of feeder During Summer and Winter Season

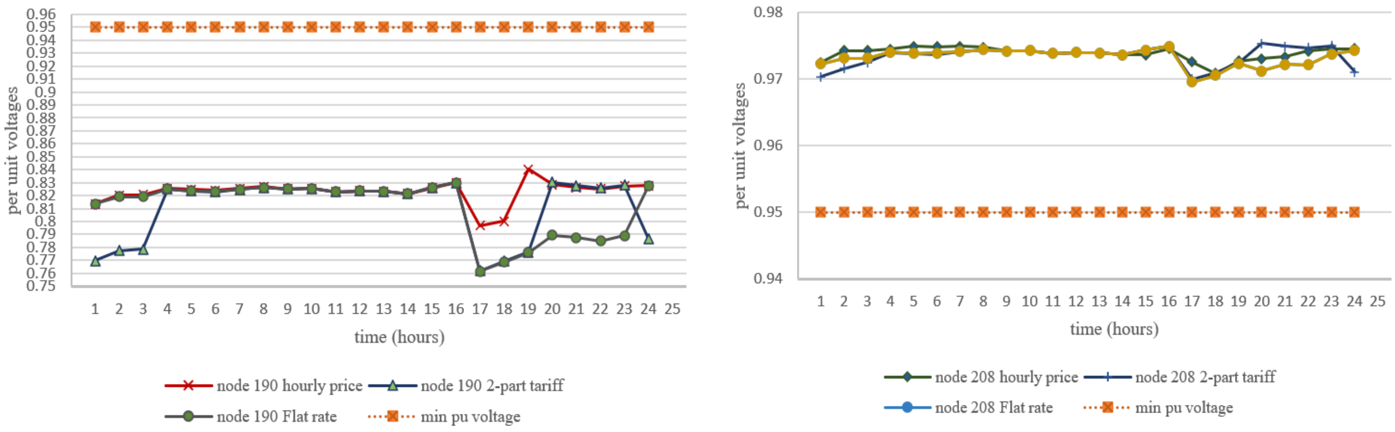
Cluster	Number of Nodes During Summer Season	Per-unit Voltage During Summer Season	Number of Nodes During Winter Season	Per-unit Voltage During Winter Season
1	192	0.97 to 0.98	190	0.98 to 0.99
2	28	Less than 0.95	25	Less than 0.95
3	81	1 to 1.01	86	1 to 1.01

By using distribution code threshold of 0.95 p.u. for under voltage and 1.05 for over voltage, it has been observed that no node is violating over voltage limit. By representing the results for all three case studies, it is identified that the voltage condition for the hourly price case is better as compared to the other two cases. Figure 1.5 and Figure 1.6 show the effect on voltage profile for 5% and 10% EV penetration in the system.



(a) **(b)**

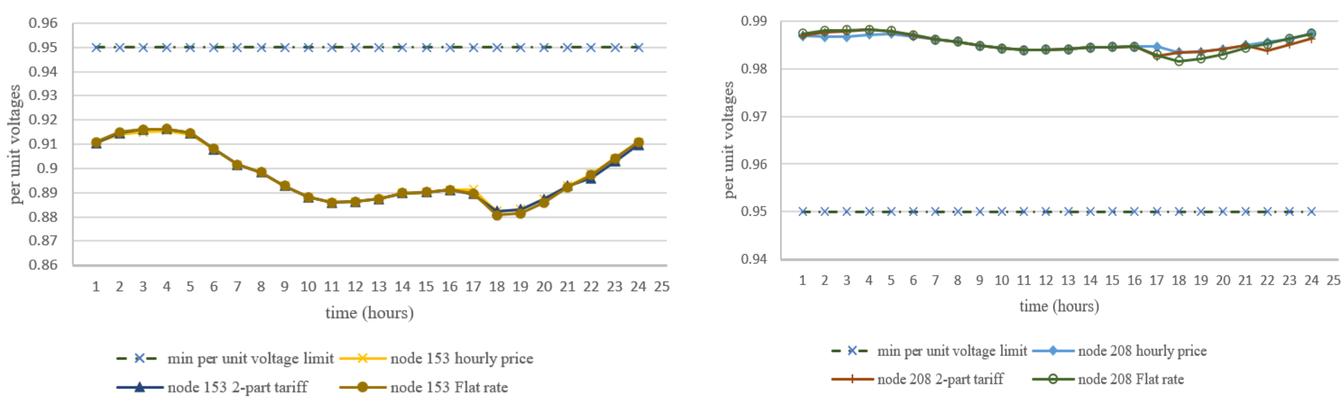
Figure 1.5: Voltage profile for 5% EV penetration during summer season (a) Node 190 (b) Node 208



(a) **(b)**

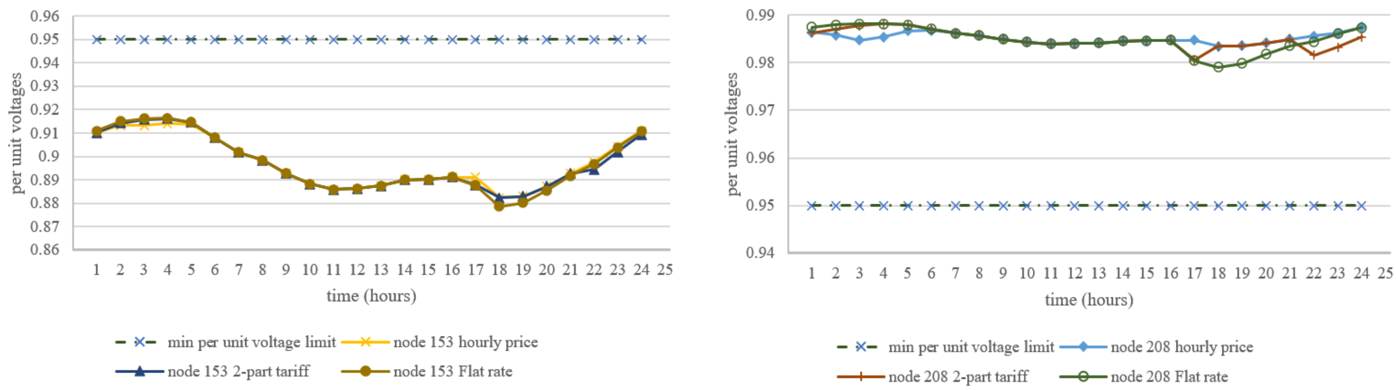
Figure 1.6: Voltage profile for 10% EV penetration during summer season (a) Node 190 (b) Node 208

Figure 1.7 and Figure 1.8 depicts that voltage profile for Hourly Price case is better as compared to other two cases and it has been observed voltage profile for winter season is better as compared to summer season.



(a) **(b)**

Figure 1.7: Voltage profile for 5% EV penetration during winter season (a) Node 153 (b) Node 208



(a) **(b)**

Figure 1.8: Voltage profile for 10% EV penetration during winter season (a) Node 153 (b) Node 208

5.4 Effect of Alternative Pricing Regimes on Hourly SOC:

Although results are available for all EVs, but for brevity only two EVs is selected to showcase how charging and discharging patterns of typical electric vehicles in our simulation change with the pricing regime. The selected EVs in summer season required 60% charge for the next day are connected in zone 1 and for winter season EVs required charging 100% for the next day and it is connected in zone 6. Two different EVs are presented to observe the different behaviors in summer and winter season as hourly price is different for both seasons.

Figure 1.9 illustrates the SOC pattern for all three case studies for the EV connected in zone 1 that required 60% charge for the next day. The charging pattern of the EV for Flat Rate is indicated by blue bars. EV reached home at 17.00 with 30% SOC, started charging right away and got fully charged by 20.00. It remained charged until 8 a.m. when the owner left home for his work. Looking at the orange bars for the 2-part Tariff case, EV started charging at 17.00 upon returning home. EV discharged between 19.00 to 23.00. (EVs cannot discharge after 20% SOC as it decreases the battery life) which are the peak hours. Subsequently, the EV started charging at 23.00 and got fully charged by 04.00.

Thereafter, the EV retained its charging level till 08.00 departure time. SOC of EV due to Hourly Price is illustrated as grey bars. Since the price is low at 17.00., the vehicle started charging ang got fully charged by 12.00. Subsequently, EV started discharging till its SOC reached 60% that is the required charging for next day. In this case vehicle get charged at low price and subsequently discharged at higher price that results financial benefit for the owner.

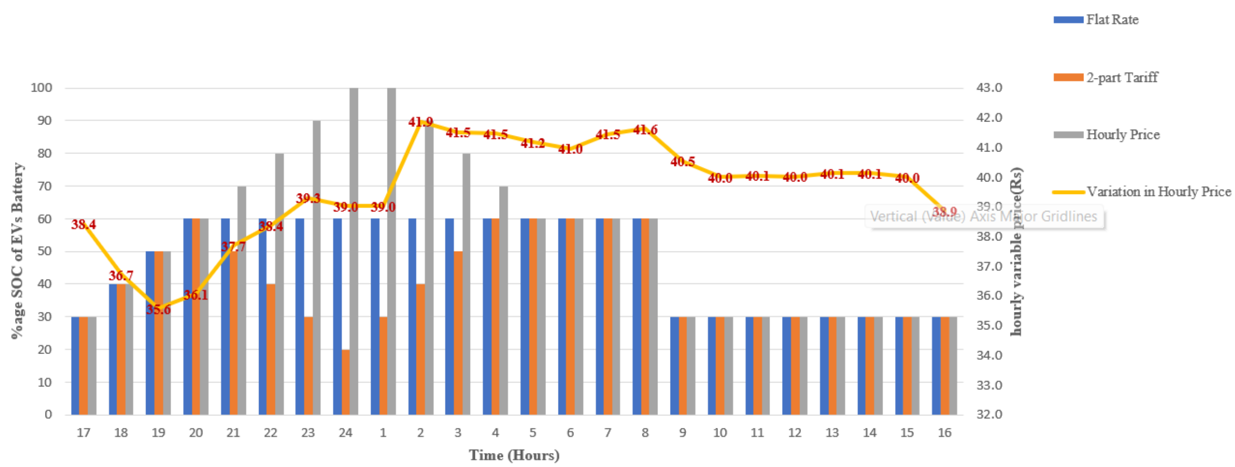


Figure 1.9: SOC Patterns of EV that required 60% charging for next day

Figure 1.10 shows the SOC pattern in winter season for all three case studies for the EV that is connected in zone 6 and required 100% charging for the next day. The charging schedule of the EV for Flat Rate is shown in blue bars. When the EV arrived home at 16.00 with 70% SOC, it began charging and was fully charged by 19.00. Owner left for his work at 08.00 till that EV remained fully charged. Orange bars in Figure 1.10 represent the 2-part Tariff case. Owner returned home at 16.00 and started charging till 17.00, then during peak hours EV started discharging till 20.00 and then again charged from 21.00. to 03.00. It was fully charged and remained 100% charged until 08.00. SOC for Hourly Price case is represented in grey bars. Since the price is high upon returning home at 16.00, the vehicle started supplying energy to the grid until its SOC reached the bottom granted level of 20% by 23.00. This EV connected for charging from 12.00 to 07.00 as prices are low and it required 100% charging for the next day.

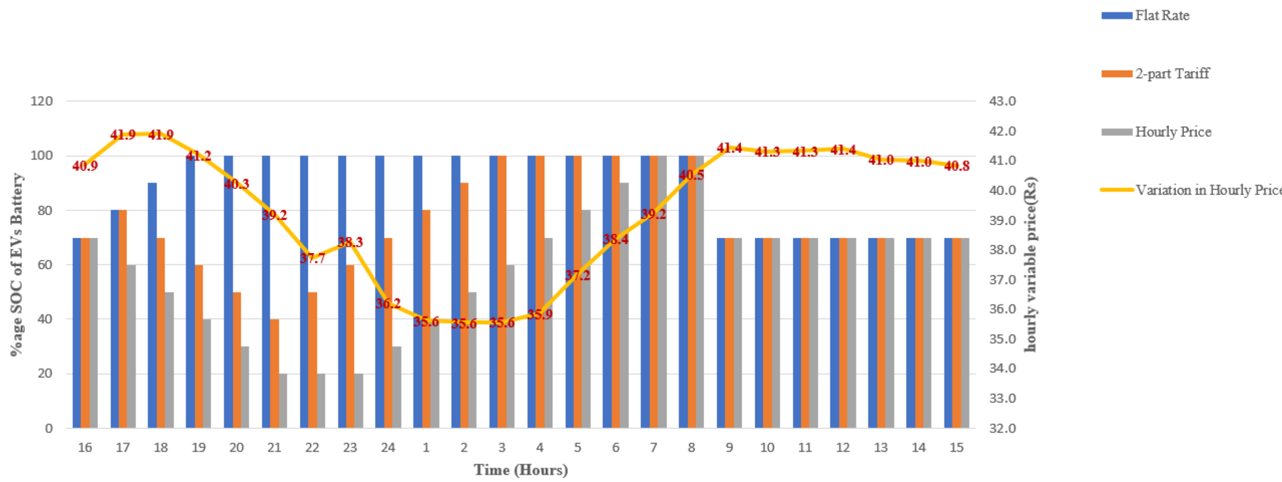


Figure 1.10: SOC Patterns of EV that required 100% charging for next day

5.5 Effect of Alternative Pricing Regimes on Cost of EVs:

One of the most important objectives of this study is to minimize the cost of EV charging. Figure 1.11 illustrate the effect of cost in case of 5% and 10% EV penetration in summer season. The purple bars show that charging cost for the 10% EV penetration is higher as compared to the cost for 5% penetration because a greater number of EVs are getting charged, in all three case studies.

Charging cost in case of Flat Rate is 3024 Rs. The charging cost decreases by 5.9% to 2845.60 Rs in case of 2-part Tariff and decreases by 18.9% to 2453.82 Rs when Hourly Price is introduced. Similarly, for the 10% penetration, cost is 6615 Rs for Flat Rate. In case of 2-part Tariff charging cost is 6224.75 Rs, it gets decreases by 5.91%. The charging cost decreases by 28.46% to 4732 Rs in case of Hourly Price. Time-varying, Hourly Price enables the least typical daily cost for charging the EVs, as owners try to charge their EVs during the least costly hours.

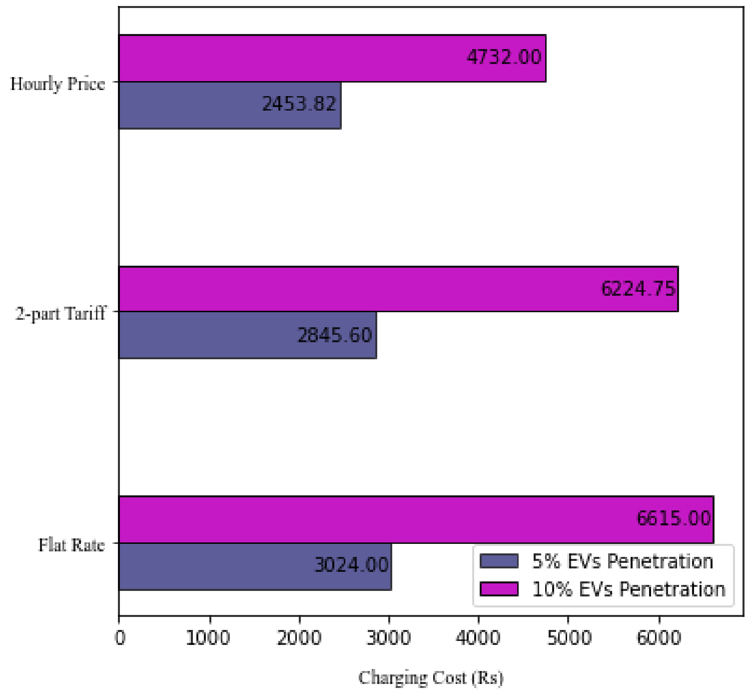


Figure 1.11: Charging Cost During Summer Season

Figure 1.12 illustrate the effect of cost in case of 5% and 10% EV penetration in winter season. By comparing the cost with summer season, it is identified that in case of hourly price charging cost decreased in winter season. For the rest of two cases, cost is same as in summer season because Flat Rate and 2-part tariff remain same for both seasons.

Figure 1.12 illustrates charging cost in case of Flat Rate is 3024 Rs. The charging cost decreases by 5.9% to 2845.60 Rs in case of 2-part Tariff and decreases by 23.24% to 2321 Rs when Hourly Price is introduced. Similarly, for the 10% penetration, cost is 6615 Rs for Flat Rate. In case of 2-part Tariff charging cost is 6224.75 Rs, it gets decreases by 5.91%. The charging cost decreases by 31.5% to 4532 Rs in case of Hourly Price.

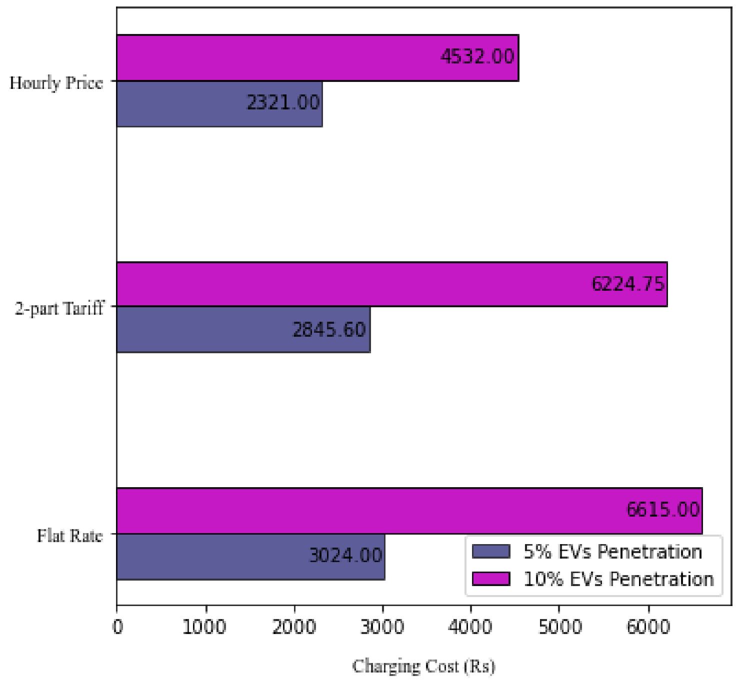


Figure 1.12: Charging cost during winter season

CHAPTER 6: CONCLUSION AND FUTURE WORKS

This research demonstrates the significant potential of smart charging with dynamic hourly pricing to address grid congestion and promote EV adoption in Pakistan. By implementing an optimized pricing model and an agent-based energy management system, the proposed solution offers cost savings for EV owners while mitigating grid strain during peak hours.

Further research could explore the integration of renewable energy sources with this system to maximize environmental benefits. Additionally, investigating consumer behavior and acceptance of dynamic pricing models could provide valuable insights for large-scale implementation. Moreover, this research emphasizes the critical role of smart charging and dynamic pricing in facilitating a smooth transition to a future dominated by EVs in Pakistan. This approach promotes the sustainable adoption of EVs by offering a win-win scenario for both EV owners (through cost reductions) and the power grid (through congestion alleviation).

Based on these findings, we recommend that policymakers in Pakistan consider the implementation of dynamic pricing models for EV charging. In addition, fostering collaboration between government agencies, distribution companies, and EV aggregators will be crucial for establishing the necessary infrastructure and consumer awareness programs for a successful large-scale rollout of smart charging solutions.

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