Agent-based modelling of electric vehicle charging for optimized charging station operation

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**NANYANG
TECHNOLOGICAL
UNIVERSITY**

SINGAPORE

**AGENT-BASED MODELLING OF ELECTRIC
VEHICLE CHARGING FOR OPTIMIZED CHARGING
STATION OPERATION**

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2019

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A thesis submitted to the Nanyang Technological University
in partial fulfilment of the requirement for the degree of
Doctor of Philosophy

2019

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

12th April, 2019

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Supervisor Declaration Statement

I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

April 12, 2019

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Date

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Assoc. Prof. Gooi Hoay Beng

Authorship Attribution Statement

This thesis contains material from two papers published in the following peer-reviewed journal where I was the first author.

Chapter 3 is published as **K. Chaudhari**, N. K. Kandasamy, A. Krishnan, A. Ukil and H. B. Gooi, “Agent Based Aggregated Behavior Modelling For Electric Vehicle Charging Load,” in *IEEE Transactions on Industrial Informatics*. doi: 10.1109/TII.2018.2823321.

The contributions of the co-authors are as follows:

- I prepared the manuscript, developed the programming model in NetLogo and performed the analysis of the results.
- Dr. Nandha Kumar Kandasamy assisted in modelling charging characteristics of electric vehicle batteries.
- Mr. Ashok Krishnan assisted in modelling IEEE-14 bus system for analysing grid impact of agent based electric vehicle modelling.
- Dr. Abhisek Ukil provided the initial project direction and edited the manuscript drafts.
- Assoc. Prof. Gooi Haoy Beng edited the manuscript drafts and provided guidance in addressing reviewer comments.

Chapter 4 is published as **K. Chaudhari**, A. Ukil, K. Nandha Kumar, U. Manandhar and S. K. Kollimalla, “Hybrid optimization for energy storage management of PV integrated EV charging station,” *IEEE Transactions on Industrial Informatics*, 2017. doi: 10.1109/TII.2017.2713481.

The contributions of the co-authors are as follows:

- I prepared the manuscript, formulated the system model, developed hybrid optimization model programming model and performed the analysis of the results.
- Dr. Abhisek Ukil provided the initial project direction and edited the manuscript drafts.
- Dr. Nandha Kumar Kandasamy edited the manuscript drafts and provided guidance in addressing reviewer comments.
- Dr. Ujjal Manandhar assisted in data collection and interpretation of the results.
- Dr. S. K. Kollimalla helped in designing the system model used for hybrid optimization.

12th April, 2019

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Abstract

Widespread adoption of electric vehicles (EVs) would significantly increase the overall electrical load demand in power distribution networks. Hence, there is a need for comprehensive planning of charging infrastructure in order to prevent power failures or scenarios where there is a considerable demand-supply mismatch. Accurately predicting the realistic charging demand of EVs is an essential part of the infrastructure planning. Charging demand of EVs is influenced by several factors such as driver behavior, location of charging stations, electricity pricing etc. In order to implement an optimal charging infrastructure, it is important to consider all the relevant factors which influence the charging demand of EVs. Several studies have modelled and simulated the charging demands of individual and groups of EVs. However, in many cases, the models do not consider factors related to the social characteristics of EV drivers. Other studies do not emphasize on economic elements. This thesis aims at evaluating the effects of the above factors on EV charging demand using a simulation model. An agent-based approach using the NetLogo software tool is employed in this thesis to closely mimic the human aggregate behaviour and its influence on the load demand due to charging of EVs.

EV charging stations where the EV charging takes place will play an important role in the energy management of smart cities. Private and commercial EV charging loads would further stress the distribution system. Photovoltaic (PV) systems, which can reduce this stress, also show variation due to weather conditions. Hence, after the successful modelling of EV charging behavior using agent based approaches, a hybrid optimization algorithm for energy storage management is proposed as an application.

This algorithm shifts its mode of operation between the deterministic and rule-based approaches depending on the electricity price band allocation. The cost degradation model of the energy storage system (ESS) along with the levelized cost of PV power is used in the case of PV integrated charging stations with on-site ESS. The algorithm comprises three parts: categorization of real-time electricity price in different price bands, real-time calculation of PV power from solar irradiation data and optimization for minimizing the operating cost of an EV charging station integrated with PV and ESS. An extensive simulation study is carried out with private and commercial EV charging load model obtained from the agent based modeling approach, in the context of Singapore, to check the effectiveness of this algorithm. Furthermore, a detailed analysis of the subsidy and incentive to be given by the government agencies for a higher penetration of PV systems is also presented. This work would aid in planning of adoption of PV integrated EV charging stations with on-site ESS which would be expected to take place of traditional gas stations in future.

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Acronyms

ABM	Agent Based Model
CP	Carpark
CCS	Combined Charging System
CC	Constant Current
CV	Constant Voltage
CPF	Cumulative Probability Function
DOD	Depth Of Discharge
DER	Distributed Energy Resources
EV	Electric Vehicles
EMS	Energy Management System
EOL	End Of Life
EMA	Energy Market Authority
ESS	Energy Storage System
FCS	Foodcentre Charging Station
GUI	Graphical User Interface
G2V	Grid-To-Vehicle
LCOE	Levelized Cost Of Energy
LB	Lower Band
OCS	Office Charging Station
OCV	Open Circuit Voltage
OPF	Optimal Power Flow
PCC	Power Coordinated Charging

PDF	Probability Density Function
PV	Photovoltaic
PHEV	Plug in Hybrid Electric Vehicles
RES	Renewable Energy Sources
RCS	Residential Charging Station
MCS	Mall Charging Station
SPM	Short Period Models
SMA	Simple Moving Average
SOC	State Of Charge
TCC	Time Coordinated Charging
THD	Total Harmonic Distortion
TOU	Time of Use
UB	Upper Band
V2G	Vehicle-To-Grid
WEP	Wholesale Electricity Price

Symbols

a	Acceleration of the EV (m/s^2)
α	Road gradient
A_{PV}	Area of individual PV panel
A_j	Frontal area of an EV of type j (m^2)
β_{pv}	Coefficient of temperature for the PV module's efficiency
B_{ESS}	kWh rating of ESS
$C_{charge,i}^k$	Cost of k^{th} charging station
$C_{run \rightarrow cs}^k$	Cost of travelling to charging station
$C_{run \rightarrow dest}^k$	Cost of travelling from charging station to the destination
C_{run}^k	Running cost of EV per unit distance travelled by the EV
$C_{d,j}$	Aerodynamic drag coefficient of an EV of type j
$C_{bd\ ch}$	Degradation cost of ESS due to charging
$C_{bd\ dis}$	Degradation cost of ESS due to discharging
C_{ESS}	Capital cost of ESS
C_g	Cost of electricity purchased from grid
C_r	Coefficient of rolling resistance for a tarmacadam road
d_{cs}^k	Distance between location of EV and charging station
d_{dest}^k	Distance between location of EV and destination
δ_{PV}	De-rating factor for PV panels
ΔSOC_{ev}^k	Change of SOC of EV between two consecutive charging events
D_k	Distance traveled by the k^{th} EV for charging after last charge
D_{maxk}	Maximum driving range of k^{th} EV based on its battery capacity

E^{ev}	Energy consumed per unit kilometer distance in kWh/km
E_b	Instantaneous energy capacity of ESS
E_{charge}^k	Energy supplied to EV from charging station
$E_{EV,j}^{min}$	Energy requirement by EV charging station at j^{th} interval
$E_{PV,j}^{max}$	Energy generated by PV system at j^{th} interval
η_b	EV battery module efficiency
η_{bc}	Charging efficiency of ESS
η_{bd}	Discharging efficiency of ESS
η_c	Efficiency of EV Converter (inside EV)
η_{conv}	Efficiency of converter for PV system
η_m	EV motor efficiency
η_{MPPT}	Efficiency of maximum power point tracking
η_{PV}	Efficiency of PV modules
E_{usable}^k	Usable energy of the EV
γ	Range anxiety index
g	Gravitational acceleration (9.8 m/s ²)
I_{cc}	Current required in constant current mode
I_{slope}	Slope of current decrements in the CV mode.
I_S	Solar irradiance in W/m^2
I_n	Charging current in constant voltage mode
J	Operation cost of total system
M_j	Mass of an EV (kg) of type j
μ	Average travel distance
N_b	Number of cycles of ESS before reaching end of life
N_{PV}	Total number of PV panels installed at EV charging station
p	Smoothing factor
P_{1c}	Power at 1C with one minute resolution
P_{Aux}	EV auxiliary power requirement
$P_{cc,SOC}$	Power required in CC mode for the EV battery pack

P_m^{ev}	Mechanical power required by the EV in Watt
P_e^{ev}	Electric power to be provided to the EV's electric motor
P_{1Cb}	Power required by ESS to charge 100% in 1 hour i.e. 1C charging rate
P_{bc}	Charging power of the batteries, seen from the grid side
$P_{bd'}$	Discharging power of the batteries, seen from the grid side
P_g	Total power supplied by the grid
P_j	Power output of PV after considering power conversion efficiency
P_L	Power demand from load
$P_{pv,peak}$	Maximum PV power generated under standard test conditions
P_{PV}	Power generated by PV system
P_n	AC power supplied to the EV battery pack
$R_{(k)}$	Electricity price
R_{cs}^n	Rate of electricity at the n^{th} charging station
ρ	Air density (kg/m ³)
SI_j	Solar irradiance during the j^{th} time interval
σ	Standard deviation in travel distance
$\sigma_R(k)$	Standard deviation of electricity price at k^{th} time period
SOC_{ev}^k	Instantaneous SOC of an EV
SOC_{UE}^k	SOC of EV associated with its user experience
SOC_{Cr}^k	Critical SOC of k^{th} EV
$SOC_{ev \rightarrow cs}^k$	SOC of EV at the instant of departure to charging station
SOC_i^k	Final SOC of the EV at the end of the charging event
SOC_i^k	Initial SOC of the EV at the beginning of the charging event
SOC_n	Increased SOC of EV battery pack
$SOC_{rise,i}^k$	% Rise in SOC of k^{th} EV at the i^{th} charging event
SOC_{usable}^k	SOC associated with usable energy of EV
τ	min/hr after which ESS degradation is calculated
$T_{benchmark}^k$	Time required to reach destination from the instant of EV departure
$T_{amb,j}$	Ambient temperature during the j^{th} time interval

$T_{amb, rated}$	Rated ambient temperature
T_{bc}	Average number of hours battery charges in a day
T_{bd}	Average number of hours battery discharges in a day
T_{est}^k	Time remaining to arrive at the destination
UF	Urgency factor
v	Speed of the EV (m/s)
ζ	Ratio of average charging time to total operating time of ESS in a day
V_{OCV}	Open circuit voltage of the EV battery pack

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Chapter 1

Introduction

In this chapter, an introduction to Electric Vehicles (EVs) and the issues arising from their integration into microgrids are introduced briefly. The research motivations, objectives, main contributions and organization of this thesis are also discussed in this chapter.

1.1 Introduction to Electric Vehicles

The history of invention of EVs can be traced back in early 19th century in the year 1835 [1]. However, due to the abundant availability of crude oil and its cheap price in the 20th century, combustion engines gained tremendous popularity in the manufacturing as well as transportation industry. This was indirectly supported by the limitations in the battery performance and lack of research in battery technologies to investigate their applications in the transportation industry. Though it resulted in fading the use of energy storage, surprisingly, the use of electric locomotives such as electric railways and electric trams were widely used in the late 20th century. With the uncontrolled use of the fossil fueled vehicles, the carbon emission levels rose across the world and the world slowly started becoming aware of the greenhouse effect. With the growing concerns over global warming, the trend in the automobile sector focused its shift from fossil fueled vehicles to the clean energy fuels. The electro-mobility emerged as the popular solution to this problem of rising level of carbon emission and drew the attention of researchers

worldwide. EVs are known to be more energy efficient when compared with internal combustion engine vehicles [2]. The total cost of EV ownership can be lower in some cases when compared with these internal combustion engine vehicles (ICEV). This triggered the extensive research activities in the battery technology which are the basic and essential building block of electric vehicles.

To date, all leading vehicle manufacturers have introduced their prototypes of all electric vehicles in the market. Many of them are already producing the plug in hybrid vehicles (PHEVs) which are the transition state between fossil fuel to all-electric vehicles. The conversion of these combustion engines into the battery-powered motored drive-train is the best solution available with the transportation industry to tackle the carbon emission problem. This has been imposed on the worldwide platform by the Paris agreement signed by the majority of the developed and developing countries [3]. Electric vehicles are not only being considered as a mode of personal transportation but it has a variety of applications such as use of autonomous electric vehicles in the hazardous areas. These vehicles are not only powered by the batteries, but also several other types of electrical energy sources like supercapacitors, fuel cells, etc. The major and promising benefits of using electric vehicles include

1. Zero emission resulting in cleaner environment.
2. High efficiency operation leading to maximum use of resources such as regenerative braking.
3. Flexibility to charge at any location with electric power supply ranging from home to public charging stations.
4. Noise free operation due to use of less non-moving parts.

Globally, a growing number of people are considering an option of purchasing EVs. In this context, an analysis on the global EV sales report [4] revealed a 59% yearly increase in EV sales in first quarter of 2018 compared to previous year. The 21st century has seen growing interest in EVs due to advances in battery technology and greater emphasis on renewable energy [2]. With greater EV penetration expected in the near

future, the demand for electricity is bound to increase as EVs require electrical energy for charging their batteries.

In addition to the above mentioned advantages, electric vehicles face several challenges which still need further research and investigations. These challenges includes the high cost of the latest battery technologies, the limited battery capacity and hence the limited range, and long recharging time. Apart from these challenges, lack of the proper charging infrastructure is the biggest obstacle in EV deployment on large scale.

1.2 EV integration into smart grid

The carbon footprint contributed by the automobile industry has become one of the major environmental concerns. The prospect of EVs is believed to be the solution to this dilemma. Most countries are setting target points to their contribution in accommodating more electric vehicles. Such policies would aid the increase of electric vehicles which eventually would justify them as distributed energy resources (DERs). EVs are fitted with the batteries ranging up to a few kWh. These EVs are charging at various charging station locations. Hence, EVs act as flexible loads which connect and disconnect at multiple nodes of a distribution grid. With ongoing research in vehicle to grid technologies, these flexible loads can be converted into flexible battery energy storage systems which can be moved among the various nodes of distribution grids. Hence, EVs can be considered as ideal DERs. Challenges in bringing EVs to the mainstream remains with concerns over charging time of the on-board batteries. In order to accommodate personal as well as commercial vehicles in the scopes of EVs, they must be provided with sufficient charging facilities. Though a viable solution to pollution reduction, these EVs pose multiple challenges in the prevailing power system. From distribution grid side, EVs are viewed as load [5]. However, simultaneous charging/discharging of large number of EVs from the grid can be a significant challenge for the power quality as well as overall grid stability [6]. Together with the increased power losses, a large number of EVs also create undesirable peaks in the distribution system [7], reducing reserve

Figure 1.1: EV charging station with rooftop PV [9]

margins, and increasing prices [8]. Authors in [8] also highlighted that without any precautionary measures, uncoordinated charging behaviors of EVs adversely add to the harmonics and disturb the balance between supply and demand, affecting the voltage control. EVs behaving as active load at times of charging eventually cause high impact on grid power quality with higher percentages of total harmonic distortion (THD). Also, it would be required to upgrade the protection schemes in some cases.

With more EVs coming on road, charging stations inside the cities, which mimic the gas station of today are the new places where EVs will be charging. These charging stations equipped with rooftop PV as shown in Figure 1.1 [9] would exhibit different operational behavior than traditional home or car park chargers. There is a need to thoroughly investigate on the EV user requirement in terms of their charging behavior, charging preferences and travel pattern and their impact on the power system.

1.3 Research motivation

An important and promising progress that is happening all over the world is the increasing integration of renewable generation. With soaring oil prices and growing concern of global warming, the electric power industry is likely to shift from conventional energy towards renewable energy generation. Renewable energy sources (RESs) such as wind and photovoltaic (PV) are weather dependent and are uncertain in nature. The heavy penetration of the PV, aggravates and complicates the electricity pricing in the

electricity market.

The electric power industry is moving toward a deregulated framework throughout the world and going towards liberalization. Since 2001, Energy Market Authority of Singapore (EMA) has progressively opened the retail electricity market to the competition to give consumers more options to manage their energy cost. Instead of purchasing energy at the regulated price from the distribution company, eligible consumers can choose to purchase energy from distribution companies under customized tariff plans or from the wholesale electricity market at the prices that fluctuate every half hour. With more liberal electricity market, end consumers can take the benefits of price variations in the wholesale electricity market. Though consumers need to meet some requirements for participation in the wholesale electricity market, newer policies are coming these days to include as many consumers as possible to trade in the wholesale market. Although there are numerous good research work which deals with electricity price, it is observed that price band allocation for the electricity market using statistical methods of economics would be more advantageous and helps in reducing complexity of optimal power flow problems.

In addition to the above, Energy Storage System (ESS) is also considered useful in reducing irregularities in the distribution system. By utilizing energy storage, generation sources need not be ramped up or down, but can instead be run at optimal efficiency while energy storage accounts for variations in the demand. The applications that could benefit from energy storage within the electric grid have a wide range of requirements. In some isolated regions, seasonal energy storage is required that needs MWh of capacity stored for months at a time. On the other end, stabilization of the transmission and distribution networks may store energy for only several minutes before releasing it. To work across all these time and energy scales, many different forms of energy storage have been developed. Due to the stressful demands on these energy storage systems, an effective management system is required to maintain safe operation and optimal performance.

Combining the rooftop PV system and ESS at the charging station with the liberal

electricity market could provide a promising solution to the issues arose from the high penetration of EVs. It could help in preventing the transfer of unwanted peaks from load side to grid side. The load from the grid can be reduced with the on-site generation and can be kept within the control by using grid-scale ESS of the size ranging upto several hundreds of kWh. Liberalized electricity markets enable charging station operator to have an economic benefits during the charging station operation by using various optimal power flow solutions. Hence, this combination can benefit in the cost effective yet optimal power flow solution to the charging station operation.

To effectively use any energy management strategy, the accurate load modelling is necessary. If the load model is realistic or close to reality the results produced by the energy management strategies could help in the application of such algorithms to real power system. Hence, the availability of the accurate load model of EV charging is the essential requirement of for practical implementation of any energy management algorithm.

To model the EV charging load, numerous methods are available in the literature. Some of the methods help in modelling the travel pattern using stochastic data while some of the methods generate the charging profiles using historical travel patterns. Various charge scheduling algorithms have been proposed by researchers across the world to efficiently apply them in real world scenarios. However, in most of the load modelling and charge scheduling algorithms, EV users are always constrained. Several researches focuses on controlling the charging power while some researchers focuses on controlling the charging time. These algorithms having delayed and slow charging mechanisms are not preferable where the commercial charging stations in future are required to replace the existing gas stations. These algorithms are highly suitable for home charging and in carparks where long duration of parking time allows the greater flexibility in controlling the loads. In today's scenario, the drivers of ICE vehicles fill the gas and leave the gas station. With the installation of fast chargers at the charging stations roadside, the drivers of EVs would expect the same characteristics from charger to recharge within a short time and continue the journey. In order to achieve such goals, chargers need to be

fast and hence algorithms compromising charging time and charging power would be less realistic.

If we intend to solve the carbon emission problem by using EVs, the majority of the gasoline car users would require to shift to EVs. Such a shift would create a need to provide the EV users the fast charging experience to the gasoline car users, they would get when they visit the gas station. This provides an additional constraints to the problem formulation such as no charging denial and minimizing the charging time by increasing the charging power. Till date, a majority of EV load modelling techniques use charge scheduling algorithms to predict the load demand. For the EV chargers fitted at the carparks, these algorithms are suitable but the commercial fast EV charging stations have a stringent constraint over the charging time. These realistic considerations from the perspective of commercial fast EV charging stations are missing in the literature while modelling the EV charging load. Apart from these constraints, there are several other factors missing in the literature which affect the charging pattern of the EV users such as charging station availability, impacts of presence of other EVs in the surrounding and influence of their actions and decisions of charging on each other to name a few. These factors are taken into consideration within a variety of transportation planning models. These models are decoupled from the power system perspective and mainly deals with the traffic network modelling. The transportation planning studies for EVs find the solution to EV penetration from the perspective of traffic planning, road network congestion and EV occupancy. The optimised models with these parameters ignore the impact of such planning on the distribution grid as these EVs need to get charged during their operation. The power system optimization studies optimize the EV penetration using the charge scheduling algorithms and optimized charging station placements in the network for reducing distribution grid impacts. This ignores the effect of presence of EVs on the road networks and road congestion. To include these factors in the EV load modelling process, the transportation models and power system models need to be co-simulated. This co-simulation studies which bridge the gap between isolated transportation studies and isolated power system studies are missing in

the literature.

Hence, before finding a solution for the optimal operation of the commercial charging station, it is a strong necessity to model the EV charging load at the commercial fast EV charging stations with inclusion of realistic transportation scenarios.

1.4 Objectives of the Research Work

The main objective of this research work is to accurately model the most realistic EV charging scenario for commercial EV charging stations and then to develop the optimized energy management strategy for the cost effective operation of single commercial fast EV charging station. To achieve this objective the study is split into two parts. The first part of this study focuses on agent-based modelling (ABM) of EV charging load at commercial fast EV charging stations and second part of this study focus on the energy management of the single commercial fast EV charging station as an application of the ABM of EV charging loads developed in the first part of the study.

The objective of the first part of the study is to provide both qualitative and quantitative insights into the charging behaviour of EV users. It aims at creating a model which examines factors influencing charging behaviours and predicts the charging demand of different types of EVs under various circumstances. The end result will facilitate an efficient process of identifying parameters crucial for influencing the loads and their impact on the total load at the charging stations. This process thereby ensures maximum utilization of the charging infrastructure for a given area with certain available conditions. The ABM process also helps in identifying the optimal charging infrastructure needs of any area under consideration of this study by analyzing the variation in charging load data.

The objective of the later part of the study is to minimize the operation cost of the EV charging station with the help of ESS using time of use (TOU) pricing which changes at half hourly basis. In order to achieve this an optimization problem is formulated based on the EV charging behaviour, battery degradation model, economic analysis of

electricity pricing of Singapore's wholesale electricity market along with various related constraints.

The optimization problem formulated in this part of the study turns out to be a linear programming problem. This problem is solved using the `fmincon` solver in MATLAB. The algorithm proposed in this study is the combination of heuristics approach as well as deterministic approach. The heuristics helps in making faster decisions as well as reducing the complexity of the problem. The deterministic approach helps in finding the optimal solution where the application of simple heuristics is not justified. Therefore, the combination of both approaches reduces the calculation time and the complexity of the problem while providing an optimal solution.

To summarize, the objectives of the study are as below:

1. Identify parameters influencing the charging behavior of EV users.
2. Develop an agent-based model (ABM) incorporating these parameters.
3. Analyze the effects of varying EV charging demand due to different charging strategies and policies.
4. Perform energy storage management for the EV charging station with ESS deployed between the grid and EV charging station and check its economic feasibility.
5. Evaluation of subsidy analysis to encourage a higher PV penetration at the charging stations.

1.5 Major contributions of the Thesis

The major contributions of this thesis may be summarized as follow:

1. This thesis proposes an ABM approach for predicting the electricity demand for EV charging. Various factors including initial State of Charge (SOC), charging duration, charging station location, charging start time, peak hours, previous charging records, varying electricity prices, types of charging, and driver experience

are considered while developing the model. Unlike previous studies, the proposed model captures human behavioural tendencies in the context of an EV owner's decision making process regarding the charging location. Finally, the model also accounts for the complex inter-dependencies which exist between these factors. The different modelling parameters are stochastic in nature. They allow the model to account for unpredictable charging behaviours.

2. The model proposed in this study provides a framework to analyze the effects of varying EV charging demand due to different charging strategies and policies. The analysis of this study shows that the penetration of commercial EVs significantly increases the EV charging load which is around 65.8% compared to the case of zero commercial EVs running in the system. The EV charging load decreases with an increase in user experience with EV driving. 28.69% load reduction is observed when EV users have more experience in driving range prediction. Moreover, the complete transition from slow charging to fast charging would result in 36.6% increase in load of single EV charging stations. This framework would, among others, help in planning the optimized sizing and locations for commercial EV charging stations across the cities based on its demographics.
3. A good charging demand forecast is the bedrock on which several power system analyses can be based. The authors have performed some preliminary power system analysis by linking the proposed agent environment with an optimal power flow problem using a modified IEEE 14-bus network. This link opens up several possibilities to study economic grid operation, charging strategies, congestion analysis and identification of overloads in the system. Strategies aimed at mitigating these issues can also be studied in depth using this platform.
4. The hybrid optimization algorithm is formulated as an application of results obtained from ABM of EV charging, in such a way that it does not require PV power forecast and EV charging load forecast. The algorithm performs optimization with real-time data, hence the optimization procedure is simplified. It is also capable of working with any kind of ESS and dynamic load, hence it is robust in nature. It

achieves all these while satisfying 100% load at all time.

5. A cost degradation model for ESS is formulated which takes into account the number of life cycles of ESS before reaching its end of useful life, and capital cost of ESS. To the best of author's knowledge, this type of ESS degradation cost formulation is not well explored in literature. Previous works on battery degradation such as [10, 11] focus on capacity fade and lifetime assessments of specifically small scale lithium ion batteries fitted inside EVs. However, the ESS degradation model proposed in this study is suitable for grid-scale applications of EV charging stations. Also, the proposed model is robust and is applicable for any kind of ESS technology and not only lithium ion batteries. Therefore, the study is reproducible with different types of ESS technologies to find their suitability for EV charging stations.
6. This thesis provides a detailed analysis on subsidy evaluation for integrating PV systems into EV charging applications. The analysis shows that for the break-even operation of a PV-integrated commercial charging station catering to privately owned EVs, around 40% subsidy in the cost of PV system is required from the funding agencies. This percentage drastically reduces to around 5% for the similar configuration of the charging station serving to commercial EVs. This reduction in subsidy is found to be the result of increase in optimised utilization of ESS during the increased load scenarios. This analysis would be beneficial in planning of economic deployment of RES and ESS for EV charging applications to achieve a higher penetration of RES in global efforts towards climate change.

1.6 Organization of the Thesis

This thesis consists of five chapters and are listed below:

Chapter 1: Introduction

In this chapter, an introduction to Electric Vehicles (EVs) and the issues arising from their integration into microgrids are introduced briefly. The research motivations, objectives, main contributions and organization of this thesis are also discussed in this chapter.

Chapter 2: Literature Review

In this chapter, basic concepts related to the EV charging process are explained briefly. The state-of-art about various modelling techniques used for modelling EV charging are discussed. Along with these detailed review of previous studies, drawback from the previous studies have been clearly identified. These drawbacks in the existing methods led to the research on the ABM technique for the EV charging modelling. Hence, the ABM technique is introduced in this chapter and its basic working along with its suitability for modelling the EV charging process is explained. In the later part of this chapter, the state-of-art methods in using the RES for EV charging stations, use of distribution grid-scale energy storage of the size of several hundreds of kWh capacity for EV charging station and the need of developing a new energy storage management algorithm for economical operation of charging station are presented.

Chapter 3: Agent-Based Modelling of Electric Vehicle Charging Load

In this chapter, the ABM approach used in this thesis to model the charging demand of EVs is explained in details. It aims at assessing the behaviour of the system as a whole. The parameters identified for analyzing EV charging behaviors are stated along with their interdependencies. These interdependencies result in the different behaviors of EV users should some of the parameters show variation. The detailed modelling process using ABM in the NetLogo environment is stated. The effect of variation in some of the major influencing parameters is presented in the later part of this chapter. This chapter

concludes with the examples of the applications of the results obtained from the ABM approach.

Chapter 4: Economic Analysis of PV-Integrated Charging Stations with On-site ESS

This chapter provides an application study of the results obtained from the proposed ABM approach in the previous chapter. An operation of a single PV integrated charging station with on-site ESS is considered for this study. The objective of this extensive economic analysis of PV-Integrated charging stations with on-site ESS is to minimize the EV charging cost with the help of ESS at a PV integrated EV charging station using TOU wholesale electricity pricing, which varies every half hour. The cost degradation of ESS is formulated in this chapter. A hybrid optimization algorithm, being combination of rule-based as well as deterministic approaches, is proposed in this chapter to meet the aforesaid objective. The wholesale electricity is first categorized into upper and lower price bands every half hour. The real-time electricity price is then checked with the real-time calculated bands, and subsequently decisions are taken by the algorithm to shift between the rule-based and the deterministic modes. Hence, the algorithm is termed as the hybrid optimization algorithm. This chapter concludes with the subsidy analysis for the high PV penetration for the EV charging stations.

Chapter 5: Conclusion and Recommendations for Future Research

This chapter provides an overall assessment of this thesis. The recommendations for the future research directions with regards to the extension of research in ABM for EV charging and the extension of energy storage management strategies for the operation of multiple EV charging stations are discussed.

Chapter 2

Literature Review

In this chapter, basic concepts related to the EV charging process are explained briefly. The state-of-art about various modelling techniques used for modelling EV charging are discussed. Along with these detailed review of previous studies, drawback from the previous studies have been clearly identified. These drawbacks in the existing methods led to the research on the ABM technique for the EV charging modelling. Hence, the ABM technique is introduced in this chapter and its basic working along with its suitability for modelling the EV charging process is explained. In the later part of this chapter, the state-of-art methods in using the RES for EV charging stations, use of grid scale energy storage for EV charging station and the need of developing a new energy storage management algorithm for economical operation of charging station are presented.

2.1 Basics of EV charging

EVs are the newer and currently the most popular mode of personal transportation in the world. With more countries focusing on reduction of carbon emission [3] and adopting renewable energy sources, use of EVs is seen as most promising solution for it. When the EVs are connected to the grid through the EV charger, the batteries inside the EVs are charged through the AC/DC power converters. These power converters can either be on-board of EV or off-board i.e. the entire power conversion is done within the charger unit or outside the EV respectively. The power level of these chargers varies with var-

ious manufacturers and regions of operation [12–14]. The driving range of these EVs is decided by the capacity of the battery fitted inside them. The components of typical EV is shown in Figure 2.1. The typical EV consists of AC/DC power converter, a battery pack, an electric motor drive and an electric motor. The AC/DC power converter is connected to electricity grid through a charging socket which varies with EV manufacturers [12–14].

Figure 2.1: Components of the typical EV

The battery capacity of EV decides the driving range of the EV. There are various types of battery technologies used by the EV manufacturers such as lead acid batteries [15], lithium-ion batteries [16] and nickel metal hydride (NiMH) batteries [17]. The characteristics of these battery technologies are summarized in Table 2.1.

With the recent progress in the lithium-ion battery technology, the other types of batteries such as NiMH and lead acid batteries are finding it difficult to find their suitability to new applications of electrical transportation. Lithium-ion batteries have been used in almost all of the recent EV models launched in last few years. The extensive research on lithium-ion batteries has drastically increased their power density and energy

Table 2.1: Characteristics of various batteries used in EV

Characteristics	Lead Acid	Nickel Metal Hydride	Lithium-ion
Specific power	100-500 W/kg	250-1000 W/kg	250-340 W/kg
Specific energy	25-40 Wh/kg	60-120 Wh/kg	100-265 Wh/kg
Cycle efficiency	50%-92%	66-92%	80-90%
Energy per unit price	7-18Wh/USD	2.75Wh/USD	2.5Wh/USD
Self discharge rate	3-20% per month	15-30% per month	2-10% per month
Cycles of operation	500-800	500-1000	400-1200

density. These higher power density and energy density ensure that the adequate energy is provided for the driving and enables the faster charging of the lithium-ion batteries. This capability of lithium-ion batteries will help in reducing the range anxiety of the EV users which has been identified as a one of the major hurdle to overcome for the extensive adoption of EVs besides their higher initial capital cost of purchase.

2.1.1 Classification of EV charging

EV charging can be classified on the basis of the rate of charging power at which the EVs are charged. The EV charging is broadly classified into two types based on the rate of charging power [18],

1. Slow charging,
2. Fast charging.

Apart from the slow and fast charging classification, the EV charging can also be classified into three levels depending on the level of the charging power supplied to EV during the charging process. These levels are Level I, Level II and Level III. Table 2.2 shows the classification of EV chargers based on their rated power supply rating.

Table 2.2: Classification of EV charging stations based on their rated output

Charger Type	Specifications		
-	Voltage	Current	Power
Level I	120V	15A	$\leq 1.5\text{kW}$
Level II	240V	$\leq 60\text{A}$	$\leq 14.4\text{kW}$
Level III	-	-	$\geq 14.4\text{kW}$

Level I and II chargers are considered as slow charging due to their relatively low power ratings and level III chargers are considered as fast chargers due to their higher

power ratings. The exact rating of charging powers may vary from manufacturer to manufacturer. The commercially available EVs in the market typically use 1C-3C as charging rate for fast charging. The one hour charging through the level I chargers provides an approximately 8km of driving range and are mostly found in residential home chargers where cars are available for a longer duration at night for charging. The one hour charging through Level II charging provides an approximately 30km of driving range and are mostly found in home as well as business car parks. The level III chargers however is usually known as ‘DC fast chargers’ use a variety of protocols and standards and they vary from manufacturer to manufacturer as well as region to region.

The Asian automobile manufacturers follow the CHAdeMo protocol [12]. The North American and European automobile manufacturers use CCS protocol to establish communication with the EV and EV chargers [13]. Apart from these two, Tesla use their own system known as ‘Superchargers’ to charge and communicate with their EV while charging [14]. These level III chargers have the capacity to charge the vehicle up to 80% of their SOC within 30 to 45 minutes. One hour charging through level III chargers provide an approximately 250km of driving range. The rated charger capacities and their respective range addition after one hour charge for the currently popular EV are summarized in Table 2.3, [19–35].

The DC fast charging is the most useful method to decrease the range anxiety of EV users [12]. However, DC fast charging brings with it an increased rate of the battery degradation [36]. It also shows some disadvantages such as voltage sags and voltage flickers in the power distribution system [36].

The slow charging can be further classified into following types [37–42]

1. Uncoordinated charging
2. Coordinated charging also known as smart charging.

If the rate of EV battery charging is $C/4$ or less, then it can be considered as slow charging. C rate is the charging rate of battery. It is defined as the portion of energy that is supplied to a battery in one hour. For example, if a battery with nominal capacity of 16Ah is charged using 2A current, then the charging rate is $1/8$ C and it will

Table 2.3: Rated charger capacities and hourly range addition.

EV model	Rated capacity of onboard chargers	Range addition km/hr
BMW i3	7.4 kW	40
Chevy Bolt EV	7.2 kW	40
Chevy Volt	3.6 kW	21
Fiat 500e	6.6 kW	35
Ford C-Max Energi	3.3 kW	17.5
Ford Fusion Energi	3.3 kW	17.5
Ford Focus Electric	6.6 kW	35
Honda Clarity	6.6 kW	35
Kia Soul EV	6.6 kW	35
Mitsubishi Outlander PHEV	3.7 kW	11
Nissan LEAF	3.3 kW / 6.6 kW	17.5 / 35
Porsche Cayenne S E-Hybrid	3.6 kW / 7.2 kW	19 / 38
Porsche Panamera S E-Hybrid	3 kW	16
Tesla Model S	10 kW / 20 kW	47 / 94
Tesla Model X	10 kW / 20 kW	48 / 94
Toyota Prius Plug-In	3.3 kW	17.5
Volkswagen e-Golf	3.6 kW / 7.2 kW	19 / 38

approximately take 8-10 hours for charging the battery based on its characteristics. The uncoordinated charging does not require any control algorithm to control the flow of power. In this method, the EVs will start charging immediately after it is connected for charging at reduced charging power.

In the smart charging method, the charging rate of each EV within the charging station is controlled using the control schemes in such a manner that the total available charging power at the charging station is optimized for the optimal power sharing among the EV chargers in operation. The criteria for this optimization depend on the problem formulations and vary widely. There are various such smart/regulated charging strategies available in literature [10, 37, 41–44]. One of the methods implemented during this process is the delayed charging method. In this method an intentional delay is added so that the aggregated charging power does not coincide with the peak demand of the distribution system. Such algorithms are suitable for car parks and residential charging stations where the cars are parked for a long duration. This provides the flexibility in controlling charging time and charging rate of each EV connected to the charger.

This is achieved by time coordinated charging (TCC) and power coordinated charg-

ing (PCC). In TCC, the number of EVs charging at a particular time at one charging station is controlled to maintain the total EV load demand within the limit of total power available for EV charging at that charging station. However, in PCC the power fed to each EV is controlled to maintain the total EV load demand within the limit of the total power available for EV charging at that charging station. Both of these methods are intended towards controlling the overall EV charging power demand within the recommended limits to reduce the impacts of EV charging on the power system operation.

2.2 Introduction to Agent-Based Modelling

In order to study the socioeconomic system, thousands of parameters and inter dependencies are needed to be studied. The process of modelling human behavior and human interaction increases the complexity of the system. The statistical analysis and the pure data driven approaches are not capable enough to completely capture the dynamics of the human interaction. Hence, there is a need of an approach which can justify the understanding of these human interactions along with the support of some statistical data. Agent-based modelling (ABM) is an interesting solution to tackle this problem. ABM helps in generating scenarios close to realistic scenario without producing the predetermined results. Agents within the ABM are autonomous, independent and can take their own decisions based on their own thinking, and interactions with surrounding agents.

The researchers across the world have tried to understand and analyze these human behavior and interactions and there is a huge variation in most of their models. These models vary from being a quantitative to a qualitative one. Some of the quantitative models are constructed in details while others are the simplified versions. The complexity of the model depends on the aim of the problem formulation and each model in literature is justified for being suitable for the purpose they have been modelled for. The less complex models enable the consideration of heterogeneity within the parameters. This leads to individuality of their decisions and behavior. However, the selection of modelling approach and extent of complexity of model depends on the application of

the model.

The traffic simulation models available in the literature are mainly microscopic in nature which shows a higher level of complexity. In these problems, the individual cars are associated with various parameters and the decision to select velocity, accelerate, steer and stop depends not only on the individual preferences but also on the surrounding cars. A detailed analysis of microscopic models helps in understanding the effect of variation in parameters on individual agents. On the contrary, macroscopic models are associated with the collective behaviour of the agents. The macroscopic models can be designed using the microscopic models by simplifying some of the assumptions and inter-dependencies.

The aim of such a modelling approach is to guide thoughts of EV users. This can be related with the example of maps. Maps are created to simplify the real data. We do not wish to see the details of every single object of the street such as traffic light poles, trees, bins etc in them. Instead, we are interested in seeing the data we want to see and depending on the purpose of each individual, it changes. Hence, we have various maps available such as street view, nearby restaurants, gas filling stations etc. Therefore the particular agent based approach can not be deemed good or bad based on the number of parameters considered and it is subjective to the problem they are going to solve using it.

The main purpose of the agent based models is to predict the behavior of the agents under certain situations. These situations can be defined as the variations in one or many parameters simultaneously. This prediction of situations should not be misunderstood as forecasting of the situation. The prediction arises from the tendencies of agents to act under certain conditions. The human aggregate may react in different ways for the same situation if occurred at the different time of the day. The forecasting can be obtained using the statistical models. In case of statistical traffic models based on vehicle usage data, travel patterns and historical breakout data, it is possible to forecast the time at which the traffic could breakout. But, the agent based traffic model can predict the behavior of drivers after the traffic breakout. Hence, it is important to understand that

the ability of agent based models is not only to forecast the scenario but also to predict the scenario and its aftereffects on the system.

The statistical forecasting models can intimate about the preparedness for the particular situation but the agent based model can assist in development of solutions to mitigate the problem. The implementation of the solutions after analyzing the problem can again be tested to see the effectiveness of the solution. This aspect of the agent based approach makes it superior to the models solely based on statistics and empirical formulations.

Based on the requirement, agents can represent an individual or group of individuals. Their interactions and inter-dependencies can be modelled using equation. These equations unlike the empirical ones are based on rule based approaches such as if-else relationships or logical operators. This kind of formulation makes the ABM more flexible. Apart from this, it is also possible to consider individual behavioral rules which give rise to ‘heterogeneity’ or collective actions of group of individuals and the random variations known as ‘stochasticity’ using this approach.

In order to understand the development of ABM we need to further understand the system of ABM. The ABM is primarily based on three components which are agents, their interactions and computation process. These components can be understood by studying the agents and the rules of governing the agents.

2.2.1 Agents

Agents in ABM are the run time software entities which are individual and autonomous in their decisions. These agents possess the attributes which influence the decision taken by them. The behavior of agents in the system is governed by the set of rules which are related to their attributes. All the agents follow the rules specified to them. However, in spite of having rules, agents are autonomous decision makers. These decisions are limited by the boundary conditions specified within the rules. The attributes of the agents are measured in terms of ‘states’. When an agent performs certain action, there is a change of state of some of its attributes. When an agent interacts with one or many

agents, the interaction process is the acquisition and communication of states of other agents based on the specified rules of interaction.

Each agent is heterogeneous and each agent has its own objective. Even if the two agents have the same states for all the attributes in the beginning of the simulation, their actions will be based on their individual decisions and the states of attributes will change according to their decisions. Further, these states of attributes will lead each agent to behave autonomously in an simulation environment. These agents are capable of learning from the decisions taken by them and actions performed in the past which influence their future actions. This makes an agent adaptive to changes in its environment.

2.2.2 Rules

Rules are the limits or boundary conditions put on the variation of states of attributes which lead to decisions in taking next action by the agent. There are several types of rules which can be defined for the agents. The rules can be simple and predefined such as agents to move ahead, turn right or left at traffic light and stop after detecting obstacle in front. The rules can be defined with the optimization objective as path tracing algorithm, path following algorithm, finding the minimum distance to charging station. The rules can also be defined with the behavioral and social interaction among the surrounding agents such as ‘car’ agents communicating with ‘charging station’ agents about initial and final state of charge of the EV battery, duration of charging, amount of power required for charging. These behavioral rules of utmost importance to understand the reaction of agents in the particular scenario or a situation of distress. These reactions assist the analysis of preventive or corrective measures to be taken to change the reaction shown by agents. The solution obtained after this analysis can be tested again to check the reaction of agents to the solution to test the effectiveness of the solution.

In a language of ABM, these rules are the procedures and agents execute these procedures to achieve the goals. These procedures can be defined in a selective way such that only a predefined agent set will follow them. The scenarios for the execution of procedures can be defined with the combination of several procedures. Some of these

procedures take the place of the top layer procedure in the hierarchy of rules to be followed by agents. The typical example would be in case of ‘car’ agents reaching nearby charging stations, only ‘car’ agents with lower battery SOC will turn for charging and the rest of the agents will continue to drive towards their goal.

2.2.3 Development of ABM

To develop an ABM, the first step is to define the system. The system is the scenario under consideration of the study. This system modelling is done by identifying what is relevant for the model and what is irrelevant for the model. A system might not have included all the parameters available in the actual system. The number of parameters and complexity of the system depends on the level of the detailed model required for analysis. Once the complete relevant system is identified, the assumptions are required to be stated in order to generate a scenario. Scenario generation technique is useful in simulating the real-life problems. These assumptions must be explicit and firm to design the boundary conditions of the system. Once the assumptions are specified the agents are designed with the attributes under consideration. The variation limits for these attributes are specified to design the decision making process of the agents. Furthermore, the correlation patterns among these attributes can be defined for the added level of complexity and study of inter dependency of these attributes as well as sensitivity analysis.

Let us take an example of ABM for EV riding in a city. The car agent possesses the attributes such as the brand of the car, battery capacity of the car, number of battery cycles used by the car, SOC of the car battery, distance to be travelled in the next few time steps, total distance covered after last charging event etc. The states of attributes in this example can be defined such as the battery capacity to be 18.8kWh, operating range of battery SOC to be 20% - 95%, driving range of EV in one complete charge to be 120km etc. These attributes can be defined during the designed stage and fixed to the certain values or they can be made available to be set in the beginning of simulation at visual interface of ABM. Thus, ABM provides a flexibility to tune the system and agents based on the requirements of the study.

After finishing the initial setting up of the system, the data is added into the model to parameterize and calibrate these attributes. These data sets help agent to learn over the course of time and influences the further decision making process. In our example of ABM for EV riding in a city, this data can be the history of life cycles of EV batteries at various rate of charging/discharging power expressed in terms of the velocity of the car, battery cycle efficiency due to various depth of discharge of batteries and historical travel patterns for anticipating the next travel pattern.

2.3 Working of ABM

After designing the system, modelling all the agents and feeding them with the data for their attributes the model is ready to be executed. The entire ABM process is represented in a block diagram shown in Figure 2.2. The first step of ABM model execution is ‘setup’ of the environment in a simulation platform. This process creates a visualization of the system modelled in the initial stage of designing. The agents are created in an environment and they assume the initial states based on the distribution formulated during the initial system design.

The ABM simulation is now ready to move towards next step. The next step in the ABM simulation is to ‘Run’ the model. Once the model has started, the simulation is executed in three steps.

First stage during the running process is to ‘initialize and update’. In this process, the agents get familiarized with the surrounding things, neighbouring agents, the position and states of their own attributes and are now ready to move ahead by taking their own decisions. The next stage of the running process is to interact with other agents and surrounding while having movement in the designed environment. The interaction process of these agents includes the exchange of information about their respective states of attributes. This makes an agent decide the course of actions it will take in the next few time steps. These actions are again subjected to change in real time, based on the further agent-interactions it might have in subsequent time steps. The final stage of the running

Figure 2.2: Block diagram of ABM process

process is to ‘Record’. This recording process can be defined as the data acquisition process. In this process, the updated states of attributes of all the agents are saved in the system for further analysis. This data acquisition process is of immense importance in ABM as this data acquisition can be used in machine Learning. It can then contribute towards the artificial intelligence of agents.

The final step of the ABM simulation is to summarize the statistics of the simulation and compile a report of the agent behavior for the further analysis. When the simulation is paused or stopped or gets completed, this report is generated. Upon further analysis the simulation can be re-run with change in attributes or modifications in the system design.

2.3.1 State-of-Art in EV charging load modelling and suitability of ABM

Various studies have been performed previously to assess the impact of EVs on the grid [45, 46]. Several reliable and accurate models have been developed to examine the

complex charging behaviours of EVs. A probabilistic constrained load flow was proposed in [47] with the inclusion of wind energy in the power system. The authors have used the queuing theory for modelling the EV plug-in time and service time at the charging station. In this queuing theory, the authors have assumed that charging/discharging of EV follows the Poisson's distribution and their service time follows the exponential distribution. These distributions are based on the predefined parameters by the authors and hence yields the desired load profiles. In [48], two different algorithms were proposed to address the issue of overwhelming peak load and its impact on grid stability. The authors of [49] proposed the use of the Monte Carlo method to model temporal and spatial transportation behaviours.

The authors of [50, 51] used a bottom-up approach for modelling EV load while the authors of [52, 53] employed a top-down approach. While both of the modelling approaches are suitable for EV load modelling, the selection of a suitable approach depends on the trade off between computation time and level of details. The bottom-up approach in simulation models allows the analysis to begin from individual elements and subsequently progress to the entire system. In top-down approach, the modelling process begins from modelling of the system and ends with the modelling individual agents. The depth of modelling depends on the level of details required for the desired problem. The top-down model helps in analyzing pattern behavior of agents while the bottom-up model focuses more on individuality of the agents. The another notable advantage of the top-down modelling approach is that it reduces the computation time for each iteration and the computation time can be altered with the level of detailing. On the contrary, the bottom-up approach consumes more computation time for each iteration compared to the top-down approach because of operation of each agent. These agent actions further trigger the responses in the system and propagate towards the top layer of the system. Hence, if the computation time and resources are not the constraints during problem formulation, the bottom-up approach provides more realistic and accurate results compared to the top-down approach.

Though many studies in literature have considered mobility patterns and electricity

prices for EV load modelling, the power demand required for charging EVs also depends on other factors such as the initial state of charge (SOC) of the EV battery, charging duration, location of the charging station, charging start time, peak hours, previous charging records, type of charging i.e. fast or slow, and driver experience. Hence, predicting the charging demand of EVs is a non-trivial problem. Various studies such as [54] and [55] have considered charging processes and EV model characteristics. However, the location of charging stations and driver's experience were neglected while simulating the EV charging load.

The authors in [56] have used the probabilistic agent-based modelling of EV charging demand to analyse its impact on distribution networks. This method allows to determine the aggregated EV charging demand. The model presented in [56] considers various EV mobility characteristics such as trips per day, distance per trip and selection of destination. The notable contribution of the work includes the response behaviour of the EV users to the inclusion of social and economic variables. Furthermore, the EV charging load generated using the proposed ABM model is tested on the 37-node IEEE test feeder adopted in the distribution grid network of Barcelona. The voltage drop occurred during this study is analysed using various charging strategies. However, after arranging the EV mobility variables, the study uses the Monte Carlo simulation method to generate multiple scenario. Implementation of this process loses the capability to change the inputs to the system in real-time and observe the adaptation of the EV users to the new scenario. Also, the study in [56] does not explain about the ABM for EV charging in details and focuses mainly on the impact of EV charging on the distribution network of Barcelona. Hence, it is essential to explore the EV mobility parameters in details during the ABM.

In [57], the authors have proposed a multi-agent based scheduling algorithm for adaptive EV charging. This is achieved by using a multi-agent system having distributed generation agents, responsive-unresponsive EV agents and EV aggregator agents. Here, the ABM coordinates the EV charging based on EV load forecasting and assigns the charging locations for EVs. Furthermore, the study also coordinates the charging lo-

cation based on availability of PV energy across the UK distribution grid. This study demonstrates the suitability of ABM in modelling and controlling the EV charging using the real-time digital simulator. The proposed charge scheduling algorithm in [57] improves the renewable energy utilization and reduces the cost of electricity consumption.

Among the different approaches available for EV load modelling, short period models (SPM) have been widely used in literature. In SPM, charging behavior is modelled with the help of fixed scenarios such as uncontrolled charging [58], delayed charging or smart charging using charge scheduling algorithms [59]. The application of these approaches include

1. To calculate the total generation capacity required for feeding an additional load demand due to EVs.
2. To analyze the generation cost for satisfying EV charging load.
3. To identify the situations where EV charging load could generate the congestion in the distribution network.
4. To assess the effectiveness of demand-response schemes used for the alleviation of these congestion due to EV charging.
5. To study the reduction in carbon emission due to EV penetration.

The use of such fixed behavior scenarios instead of explicit modelling highlights a strong limitation of such models. The major drawback of these models is that they yield predetermined results of charging demand. This means that the accuracy of results due to the incorporation of certain charging strategies and policies is presumed during modelling. The model follows the predefined process to arrive at the conclusion. Instead, modelling should be explicit to test the effectiveness of different charging strategies or policies.

Furthermore, a failure to consider travel patterns in these models results in randomness not being captured which reduces model flexibility and responsiveness to various policies. The authors in [60, 61] have used the archetypal driving patterns which are

generated from the summary of driving survey. The statistics in these studies are based on the real town survey. In the survey, each archetype has been defined with the specific parking time at home and work along with the trip duration between them. This approach of modelling has successfully captured the travel pattern but the model could not capture the travel pattern variability which comes from the individual decisions of each EV user such as variable start and end times, variable trip duration arising from different driving speeds etc. This is the strong limitation of the presented model. The authors of [62] used the 'Feathers' software for an activity based model to generate the 24h charging demand. For this, the authors assigned a capacity equivalent to ICEVs to their agents and mapped the energy consumption equivalent to it. However, this model is not sensitive to electricity prices because the travel schedules are generated from independent ICEVs. The analysis presented does not evaluate the effect of charging strategies on travel patterns and vice versa.

Another common practice to model the EV charging load is to use the Markov chain modelling approach [49, 63]. This approach is usually used during the reliability study to generate the long term scenarios. These models are typically not modelled in details as they are mainly considered as load demand generating approaches for further power system studies. One of such an interesting model is presented by the authors in [63]. The authors in [63] have developed the one year vehicle state Markov chain model to generate the EV pattern. The state of each EV is defined in each 30-minute interval for a period of one year. These states includes driving data, parking at residential spaces and parking at office spaces. The initial and interim states are derived from the statistics of travel pattern in Portugal. However, the link between the decision making and calculating the travel demand based on the variable outcomes of such decisions is missing in such models. The complete dependency on empirical formulations makes the Markov chain model difficult to capture the response of EV users for change in travel conditions and policies.

ABM has been used in many power system applications. The authors of [64] modeled distributed renewable energy generation and demand as different agents. The en-

energy transaction mechanism in power markets was extended for these agents. The approach reduced energy purchase costs by tracking the forecasted energy consumption and generation. In [65], each distributed energy storage (DES) was modelled as an agent. The communication between these agents was implemented through the dynamic average consensus method to retrieve the average SOC of DES. In [66], the authors developed a price based demand response procedure for day-ahead planning and decision-making in retail electrical energy markets using an agent-based framework. Here, the ABM approach was used to address issues of inter-operability and data privacy in retail power markets.

The ABM approach provides a scope to add different charging behavior preferences due to various policies and facilitates a study on the effect of such policies on charging demand and charging station planning.

2.4 Optimization of charging station operation

After modelling the realistic EV charging load, for the optimized operation of charging station and to provide the same experience to EV owners as that of gas stations, a proper operational model of the charging station is necessary. The charging station must be ready to absorb any charging demand arriving at the charging station and should be able to perform energy management to provide such an experience. Many researchers have worked in this direction with various objectives in their study. The EV charging station in this work is considered to have a lithium-ion energy storage system and rooftop PV panels covering the entire parking lot of the charging station. The overview of various charging optimization and smart charging algorithms, ESS energy management algorithms and the use of RES for the EV charging station is provided as below.

2.4.1 Algorithms for optimized operation of charging stations

From the load point of view and for reducing the problems arising due to EV charging, most of the recent research works focus on coordinating the EV charging. The authors

in [7] aim for minimizing power losses and reducing voltage deviation, while authors in [67] describe maximizing the power delivery without adding burden to the existing grid. Various charge control methods are also proposed by the authors in [59,68].

To achieve sustainable integration of transportation and electric network, the authors in [69] have proposed intelligent scheduling of EVs as loads and sources, whereas charging and discharging costs of the EVs are minimized in [70] for overnight demand shaping. EV charging scheduling is also implemented in [71] with particle swarm optimization under dynamic electricity pricing. The author in [68] proposes a two stage mechanism for massive EV charging in which a fast charging rate compression algorithm being implemented for EV charging optimization. However, this may increase the charging time for the EVs.

Many researchers have carried out energy storage management for integration of EVs into the grid. To date, most of them mainly deal with energy storage management of batteries inside EVs. In [10], charging/discharging of lithium-ion battery inside EV is controlled in order to adjust to the grid variability. The authors in [72] proposed various charge scheduling algorithms for EV charging in the grid-to-vehicle (G2V) scenarios and vehicle-to-grid (V2G) scenarios. In all these scenarios, the EV charging time is always compromised.

The drawback identified from the [48,68,72] is that EVs have to wait or charge with low charging power due to charge scheduling algorithms. However, this is not a practical solution when a large number of EVs will penetrate. It is also not realizable in real world if we consider today's scenario, where gas stations fill the cars immediately and as required. Such gas stations will be replaced by the charging stations in future, customer expectations remaining the same. The focus in this study is given on the consideration that there should not be any delay in the charging event of EV once it is connected to charging station. However, this problem can be tackled using an energy storage system for the EV charging station. This will serve as a buffer between the grid and the EVs. Also, EVs should not to be kept waiting for long hours to get charged. Another advantage of deploying ESS between the grid and EVs is to utilize variations in the electricity

prices of the wholesale electricity market, optimizing the cost-effectiveness of the ESS for this application.

2.4.2 Renewable energy integration for charging stations

In majority of the literature, EV charging load is mainly fed by the distribution grid, for which conventional generation units are the major sources. This surpasses the actual intention of adopting EVs as a green solution, as power fed to these EVs is taken from non-renewable energy sources. This adds to carbon footprint. According to Paris Agreement on Climate Change, more than 180 countries have agreed to take initiatives towards reducing the global warming and increasing the share of green energy sources [3]. To achieve this, Singapore has planned to raise the solar power generation to 350MWp by 2020, representing about 5% percent of peak electricity demand [73]. Falling prices and continued market demand are expected to accelerate the adoption of solar energy. Hence, the use of PV as much as possible for charging EVs at charging stations would be the true green solution in reducing carbon footprint. The RES-based EV charging station especially PV integrated one is the critical problem, which is not well explored [2], and needs to be analyzed further.

2.4.3 Energy storage integration for charging stations

With the rapid growth in dynamic loads such as EV charging, there are three major requirements from the distribution side,

1. Ability to store the energy in the source or grid during surplus on-site generation and off-peak load demand.
2. Ability to supply the energy to EV charging stations during peak demand and deficiency in on-site generation capacity.
3. Ability to change the role from energy storage to energy provider and vice versa, during power transfer operation within each wholesale electricity market price change duration i.e. 30 minute case of Singapore.

Lithium-ion based ESS fulfills all of the above-mentioned requirements for integrating an EV charging station load into the existing system. While implementing energy storage within the grid has many benefits, the cost of the storage unit must be taken into account. The inclusion of an ESS will incur the additional cost associated with storage [74, 75]. The benefit of the ESS to any energy system requires an analysis on economic viability of ESS in that system. A proper economic analysis needs the construction and the operating cost to be compared against the predicted profitability of the ESS in operating conditions experienced at the installation-site. Through a better understanding of the costs and financial benefit provided by a grid-connected ESS, power system operations optimize their systems for easier integration of ESS systems into their grid. Improper management of the ESS can incur large costs for the operator due to improper charging and discharging times. The hybrid optimization algorithm proposed in this study optimizes the operation of ESS for economic cost and benefit.

2.5 Summary

EV is the popular choice of personal transportation mode today. This popularity of the EV has resulted into the increased charging operations throughout the power distribution network and hence it has started impacting the distribution grid [36]. Based on the charging power of these EVs, it can be classified into slow and fast charging [37–42]. The slow charging usually takes place overnight at home while the fast charging operation is seen at the carparks and commercial EV charging stations. The charging operation can also be classified as uncoordinated and coordinated charging based on the control techniques implemented over them [10, 37, 41–44]. The controlled charging usually increases the charging time of the operation making them less suitable for the commercial EV charging purpose. The uncoordinated charging operations observed at the commercial fast charging stations are the major reason behind instability of distribution grid. In order to mitigate such impacts on the distribution grid, the accurate and realistic EV charging modelling is necessary.

Among the various approaches used in literature for EV load modelling, SPM is most widely used model [58,59]. These models are scenario specific and generate the accurate representation for the particular scenario they are modelled for. The major drawback of these models is that they yield predetermined results of charging demand. This means that the accuracy of results due to the incorporation of certain charging strategies and policies is presumed during modelling. The model follows the predefined process to arrive at the conclusion. Instead, modelling should be explicit to test the effectiveness of different charging strategies or policies. Similarly, the models discussed in [41, 76–78] follow various modelling techniques for EV load modelling but result in the modelling efforts towards a desired conclusion.

To avoid such deliberate modelling, ABM has been identified as one of the most promising techniques. ABM has been a popular modelling technique in the field of power systems [50–53,56,57,64–66] where the agents are fed with the decision making ability, co-relations and probabilistic models to react on multiple scenarios. The distinguishing feature of ABM is the communication and evolution ability of agents during the simulation. This enables agents to adapt to policy changes based on community behavior and react independently.

There are several other factors missing in the literature [45–49] which affect the charging pattern of the EV users such as charging station availability, impacts of presence of other EVs in the surrounding and influence of their actions and decisions of charging on each other to name a few. These factors are taken into consideration within a variety of transportation planning models. Transportation models are decoupled from the power system perspective and mainly deal with the traffic network modelling. The transportation planning studies for EVs find the solution to EV penetration from the perspective of traffic planning, road network congestion and EV occupancy. The optimised models with these parameters ignores the impact of such planning on the distribution grid as these EVs need to get charged during their operation. The power system optimization studies optimize the EV penetration using charge scheduling algorithms [7, 59,67–71], ESS [10, 72] and renewable [2, 3, 73] and, optimized charging

station placements in the network for reducing distribution grid impacts. This ignores the effect of presence of EVs on the road networks and road congestion.

To include these factors in the EV load modelling process, the transportation models and power system models need to be co-simulated. This co-simulation studies which bridge the gap between standalone transportation studies and standalone power system studies are missing in the existing literature. The proposed ABM for EV charging tries to bridge this gap by considering transportation factors along with power system constraints. The detailed explanation of these factors along with the ABM is presented in Chapter 3.

Chapter 3

Agent-Based Modelling of Electric Vehicle Charging Load

3.1 Introduction

In this chapter, the ABM approach used in this thesis to model the charging demand of EVs is explained in details. It aims at assessing the behaviour of the system as a whole. Agents are autonomous, able to interact with each other and react to stimuli to achieve their goals. The functioning of the system is not determined by design. Instead, it is the result of the spontaneous and natural conduct of agents in the environment [79]. The final aim of the ABM approach is to find explanatory insights through the assessment of the collective behaviour of agents in their natural environments rather than finding practical solutions or solving engineering problems by designing agents in a deliberate manner. The spontaneous nature of the ABM approach allows the prediction of human charging behaviour based on the different parameters assigned. The model simulates and defines each EV through its charging characteristics, mobility pattern and vehicle type. This creates an interactive environment where decision making and dissimilar circumstances are inculcated to produce a realistic model that predicts charging demands of individuals as well as groups of EVs. To briefly summarize, the advantages of the proposed ABM for EV charging include

1. The non-deliberate reaction of EVs to the stimuli based on their previous history of interactions with other EVs and EV charging stations.
2. Observation of EV parameters, EV interactions and EV movements on microscopic level.
3. Study of influence of various signals such as electricity price, road congestion, charging station availability etc. on the charging behavior of the EVs.

However, the ABM for EV charging also has some drawbacks. The efficiency of the ABM is heavily dependent on the resource availability. The simulation of microscopic model for EV charging behaviour requires large memory and it consumes more energy as well as computational resources. This limitation of the microscopic ABM could be avoided by using the macroscopic model for ABM. The macroscopic model consumes lesser computational resources and requires less memory for its execution but the scope of details to be observed is heavily compromised. This drawback is not associated with the process of ABM but constrained by the resource availability. Hence, the type of ABM to be used for EV charging applications depends on available computational resources. In this study, the model is simulated using the NetLogo software package [80] which is well suited for complex systems analysis as it allows interactions among agents. Thousands of agents can receive instructions simultaneously and operate independently. The connections between macro and micro mobility patterns that emerge from agent interactions can be used for understanding EV charging behavior thereby leading to the development of a hybrid modelling approach. With the inclusion of a proper setup and all the factors which influence the load model, it allows the charging demand to be analyzed. This study has used the data and statistics in the context of Singapore to test the proposed modelling approach. The detailed modelling process of NetLogo can be referred from these books [81, 82].

Figure 3.1: Inter-dependency of EV charging system parameters

3.2 Types of model

Human aggregate modelling within the ABM has become an effective tool to simulate aggregate movement and behaviour in real life. Many researchers have used microscopic and macroscopic modelling approaches for dynamic environments. The macroscopic model focuses on the overall pattern behaviour of the whole human aggregate and increases simulation efficiency while the microscopic method focuses on characteristics of individuals such as decision making and captures the accuracy of individualistic behaviours [83]. In NetLogo, it is possible for these two models to co-exist in order to leverage on the individual strengths of both models.

The agents (EVs) in this model have their own specifications and make decisions based on their objectives. For instance, the EV starts to look for charging stations whenever the SOC of its battery falls below 25% (a variable in the model whose value can

be changed to carry out detailed analysis). This demonstrates the microscopic nature of the model as EVs act individually and make decisions based on their own specifications. On the other hand, this behaviour is constrained by the overall movement of the human aggregate. For example, an EV user cannot charge at a charging station if it is fully occupied. The parameter ‘Charging station availability’ is determined by the presence of other EVs at the charging station. If all chargers at a particular charging station are fully occupied, EV users can either decide to queue and wait or find other charging stations. This would further reduce the SOC of their batteries. These EVs would not only influence and add to the load at other charging stations but also increase the amount of energy required for their charging and charging duration. These two parameters would then influence the ‘Charging station availability’ parameter for other EVs at various charging stations. This chain effect is triggered by the action of a single EV and affects other EVs in its vicinity.

Another example would be during the night when most private cars are parked overnight instead of being driven on the roads. Such a behaviour is considered on the macro level as the EVs account for the presence of other EVs; interact with each other and behave on a large scale. This discussion emphasizes the need for this study as the usage of the proposed model enables a comprehensive coverage of factors at individual/micro and collective/macro levels.

Figure 3.1 shows the micro level decision variables in ‘circles’ and macro level decision variables in ‘squares’ along with their inter dependencies in decision making for charging EVs by the owners.

3.3 Micro level parameters

These parameters are associated with the individual behaviour of each EV and its driver. Variation in any of these parameter triggers the series of changes in other parameters.

3.3.1 Category of EV

The EVs are classified into two categories - private and commercial. Private EVs are similar to the personal vehicles while commercial EVs mainly comprise electric taxis, electric freight trucks, electric buses etc. In this study, we have considered only electric taxis as commercial vehicles due to recent government initiatives in deploying electric taxis in Singapore [84]. Such a categorization is necessary to distinguish between different behaviors exhibited by vehicles in each category. Private EVs can be modelled using trends of office hours and car park statistics at residential complexes and shopping malls. Electric taxis tend to operate for 24h with different shifts. Hence, the approach used for modelling private EV models cannot be used for modelling electric taxis.

3.3.2 Initial SOC, (SOC_i)

The initial state of charge, SOC_i , is the SOC of EV when it arrives at the charging station for charging. The initial calculation for electric taxis is based on the average daily ridership, average distance per passenger-trip and total number of taxis in Singapore. The average daily distance traveled by taxis in Singapore is 280km as per data provided by LTA [85]. Taxis need to be charged at least twice per day by considering the maximum range of EVs available in the market. It is assumed that the average distance traveled by the vehicles follows a normal distribution [54]. The normal distribution function is given by eqn. 3.1.

$$P(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (3.1)$$

A typical probability density function (PDF) and a cumulative probability function (CPF) of an average travel distance (μ) of 280km and standard deviation (σ) of 50km are shown in Figure 3.2

The initial calculation for private EVs is based on the private vehicle annual mileage and total number of private vehicles in Singapore. The average daily distance traveled by private vehicles in Singapore is 50km as per data provided by LTA [85]. Private

Figure 3.2: PDF and CPF with average traveling distance of 280km and standard deviation of 50km.

vehicles are majorly used for trips such as home to office and home to leisure places. Hence, private EVs with range of 100s of km are not required to charge on daily basis. These types of EVs also show more flexibility and have potential to response favourably to time-of-use pricing. Similar to the electric taxis, it is also assumed that the average distance traveled by the private vehicles follows a normal distribution [54]. The normal distribution function is given by eqn. 3.1 with an average travel distance (μ) of 50km and standard deviation (σ) of 10km.

Assuming that the same charging power is used, the charging duration naturally increases with a lower SOC_i . EV owners would normally prefer to charge their batteries to at least 80% SOC before leaving the charging station. Thus, with a lower SOC_i , a longer duration is required for EVs to complete charging. In this simulation study, SOC_i is initially allocated as a random value following a normal distribution stated in Figure. 3.2 and eqn. 3.2.

$$SOC_i^k = (1 - \frac{D_k}{D_{maxk}}). \quad (3.2)$$

In eqn. 3.2, D_k is the distance traveled by the k th EV for charging after last charge

in a day estimated with the previous vehicle traveling data and probability distribution from Figure 3.2, D_{maxk} is the maximum range of k th EV of N EVs available for charging as shown in Table 3.2 [19–21].

In the subsequent event of charging the SOC_i is calculated based on the actual distance travelled by the vehicle, velocity of the vehicle during charging, aerodynamic resistance to the vehicle etc. This process of calculating SOC_i in subsequent interactions during simulation is explained in details under the subsection, ‘3.3.3 Final SOC (SOC_f)’.

3.3.3 Final SOC (SOC_f)

SOC_f is the final SOC of the EV after at the end of a charging event. It depends on the type of EV and the total distance the EV owner intends to travel before the next charging event. It is assumed that commercial EVs will always attempt to get a full charge i.e. above 80% and close to 100% in minimum time. This assumption holds true as the commercial EVs such as electric taxis will be operating in shifts and drivers will try to maximize their earnings during their shift times. There are several ways to calculate and estimate the values for SOC_f . For private EVs, the distance travelled by an EV after the last charge can be estimated based on a typical PDF with an average travel distance of 280km and standard deviation of 50km calculated from eqn. 3.1 and 3.2. For commercial EVs, the SOC_f can be obtained from the random distribution between 80% to 100%. It can also be deduced from the historical charging preferences of EV users. It is also possible for EV users to enter the desired SOC_f in the simulation platform in real-time using graphical user interface (GUI).

The SOC of an EV (SOC_{ev}^k) varies from the SOC after it leaves a charging station at the end of one charging event (denoted by SOC_f) to the SOC when it reaches a charging station for the next charging event (denoted by SOC_i) based on the speed and acceleration of the EV as described in the following paragraphs.

When the vehicles moves in any direction, various forces act on the vehicle due to gravity, friction and wind resistance. When the vehicle moves in longitudinal direction,

the major forces acting on the it include: the rolling resistance of the front and rear tyres, aerodynamic drag, grade climbing resistance and acceleration resistance [86]. The horizontal force acting on the wheel centre in the direction opposite to the movement of the wheel is called the rolling resistance. A vehicle traveling at a particular speed in air encounters a force resisting its motion. This force is known as aerodynamic drag.

When a vehicle moves up or down a slope, its weight creates a force component of that is always directed downwards. The force component opposes the forward motion during climbing. When the vehicle moves down the grade, this force component assists the motion of the vehicle. This force is called the grade resistance. On the top of these forces, an additional inertial force acts on the vehicle during acceleration and breaking operation. This force acting on the vehicle due to its total mass and inertial mass is called the acceleration resistance.

Based on these road forces acting on the EV, the mechanical power required by the EV P_m^{ev} in watts can be calculated as follows [86]:

$$P_{m,k}^{ev} = M_j a_k V_k + M_j g (V_k \sin \alpha + C_r \cos \alpha) + \frac{1}{2} C_{d,j} A_j \rho V_k^3 \quad (3.3)$$

where M_j represents the mass of an EV (kg) of type j ; V represents the speed of the EV (m/s); a represents the acceleration of the EV (m/s^2); g represents gravitational acceleration ($9.8 m/s^2$); $C_{d,j}$ represents the aerodynamic drag coefficient of an EV of type j ; A_j represents the frontal area of an EV of type j (m^2); ρ represents air density (kg/m^3) and C_r represents the coefficient of rolling resistance for a tarmacadam road. These equations are generated using the basic of dynamics of EVs [86,87] . Further, α represents the gradient of the road whose value is taken as 0 in this work. In other words, the roads considered in this work are assumed to have zero gradient. The road gradients at different locations can be easily modified subject to the availability of data from the relevant authorities. Table 3.1 provides the values of all the parameters used in eqn. 3.3 for the three types of EVs considered in this work - BMW i3 [19], Nissan Leaf [20] and Kia SoulEV [21]. All the time varying variables are denoted using $(\cdot)_k$ during minute k .

Based on the mechanical power required, the following equation calculates the elec-

Table 3.1: Mechanical parameters for EV discharge power calculation

M_{i3}	1415 kg	A_{i3}	2.8 m^2	$C_{d,i3}$	0.29
M_{Leaf}	1500 kg	A_{Leaf}	2.74 m^2	$C_{d,\text{Leaf}}$	0.28
M_{Soul}	1580 kg	A_{Soul}	2.51 m^2	$C_{d,\text{Soul}}$	0.35
ρ	1.196 kg/m^3	C_r	0.025	α	0
P_{Aux}	700 W	η_b	90%	η_m	93%

tric power to be provided to the EV's electric motor (P_e^{ev}) by factoring in the motor efficiency (η_m), EV auxiliary power requirement (P_{Aux}) and battery efficiency (η_b):

$$P_{e,k}^{\text{ev}} = \frac{P_{m,k}^{\text{ev}}}{\eta_m} + P_{\text{Aux}} \quad (3.4)$$

$$SOC_{\text{ev}}^k = SOC_{\text{ev}}^{k-1} - \frac{P_{e,k}^{\text{ev}}}{\eta_b B_{\text{ev}} \cdot 60} \quad (3.5)$$

$$\Delta SOC_{\text{ev}}^k = \frac{P_{e,k}^{\text{ev}}}{\eta_b B_{\text{ev}} \cdot 60} \quad (3.6)$$

$$SOC_i = SOC_f - \sum_{k=0}^N \Delta SOC_{\text{ev}}^k \quad (3.7)$$

where N represents the number of samples during the total duration of the trip.

The energy consumed (E^{ev}) per unit kilometer distance (d) travelled by the EV during its last trip can be calculated in kWh/km as follows:

$$E^{\text{ev}} = \frac{1}{60000} \frac{\sum_{k=0}^N P_{e,k}^{\text{ev}}}{d \eta_b} \quad (3.8)$$

3.3.4 Mode of charging

The EV charging can be classified into slow and fast charging mode. In the proposed model, EVs can choose between fast or slow charging depending on the category of EV as well as the distance and time remaining to reach the destination. The slow charging process in this study is considered as Level 2 charging with each slow charger at the

charging station rated at 6.6 kW capacity. The fast charging process considered in the study as DC fast charging with each DC fast charger at charging stations rated at 50 kW capacity.

The mode of charging affects the charging duration of individual EVs. This will further affect the occupancy of charging stations and influences the decisions taken by other EV agents in selecting charging stations.

3.3.5 Charging time

A longer charging duration results in the charging slot being occupied for a longer period of time. Other EVs that intend to charge may in turn re-route or travel longer distances in search of charging stations with vacant charging slots. This causes a further reduction in their SOC_i values. The charging time parameter acts at both microscopic and macroscopic levels. Three different types of EVs namely, BMW i3 [19], Nissan Leaf [20] and Kia Soul EV [21] are used in the proposed model and their details are provided in Table 3.2. Their SOC variation w.r.t. time is shown in Figure 3.3.

Figure 3.3: SOC variation of EV batteries during charging

The open circuit voltage (OCV) of the battery pack was obtained from the standard battery models available in MATLAB-Simulink [88] and curve fitting (smoothing spline) was used for deriving a relationship between OCV and SOC.

$$V_{OCV,SOC} = f(SOC) \quad (3.9)$$

Table 3.2: EV Battery specifications

EV Model	Battery Capacity B_{ev}	P^{ev} (Fast)	P^{ev} (Slow)
BMW i3	18.8 kWh	35.89 kW	5.4 kW
Nissan Leaf	24 kWh	38.76 kW	6.3 kW
Kia SoulEV	27 kWh	39.1 kW	5.1 kW

where f is given by,

$$\arg \min f, f = \sum (V_{OCV} - f(SOC))^2 + (1 - p) \int \left(\frac{d^2(SOC)}{df^2} \right)^2 d(SOC) \quad (3.10)$$

where p represents the smoothing factor. p can be varied between 0 and 1 for adjusting the smoothness of the fit wherein 0 results in a linear fit and 1 results in a piece-wise cubic polynomial fit. Furthermore, p can also be selected as $\frac{1}{\left(1 + \frac{h^3}{6}\right)}$ where h represents the average difference between the data points.

Let I_{cc} be the current required in constant current (CC) mode. $P_{cc,SOC}$, which represents the power required in CC mode (for a particular SOC) is given by the following equation:

$$P_{cc,SOC} = V_{OCV,SOC} \cdot I_{cc} \quad (3.11)$$

The charging current in constant voltage (CV) mode at time instant n is given by the following equation:

$$I_n = I_{n-1} - I_{slope} \quad (3.12)$$

where I_{slope} represents the slope of current decrements in the CV mode. I_{slope} is a fixed value determined based on the EV characteristics and calculated from the time required in the CV region for each EV [19–21]. The charging power required in CV mode is calculated as follows:

$$P_{cv,SOC} = V_{OCV,SOC} \cdot I_n \quad (3.13)$$

The charging power at any time instant n is given by the following equation:

$$P_n = \frac{P_{b,n}}{\eta_c} \quad (3.14)$$

where P_n represents the AC power supplied and η_c represents the converter efficiency (considered as 0.95). $P_{b,n}$ can be either $P_{cv,SOC}$ or $P_{cc,SOC}$ depending on the status of the EV battery.

The SOC increment is calculated using the following equation:

$$SOC_n = SOC_{n-1} + \left[\frac{P_n}{P_{1c} \cdot 60} \right] \quad (3.15)$$

where SOC_n represents the increased SOC; SOC_{n-1} represents the SOC before supplying P_n and P_{1c} represents the power at 1C with one minute resolution.

Using the above equations, the charging curve of an EV can be generated and the charging time can be determined based on the number of samples. For fast charging, typical charging powers and charging times are shown in Figure 3.4 for the three vehicles - Kia Soul EV, Nissan Leaf and BMW i3 considering SOC_i as 20%. All the three EVs were connected to 50kW DC fast chargers for this process. The charging power for these EVs from 20% to 80% of SOC remains around the 50kW. The charging power shows a slight uptrend but the ramp rate is negligible. After the SOC of EV reaches 80% the charging power drops significantly. For Nissan Leaf the charging power drops to 26kW at the end of the 28th minute. For Kia Soul EV, the charging power drops to 29.5kW at the end of the 33rd minute. For BMW i3, the charging power drops to 35.5kW at the

Figure 3.4: Fast charging characteristics of EV batteries

end of the 39th minute. The charging power for all of these vehicles starts gradually dropping to zero kW as SOC of the vehicle approaches 100%.

For slow charging, the typical charging powers and charging times are shown in Figure 3.5 for the three vehicles - Kia Soul EV, Nissan Leaf and BMW i3 considering SOC_i as 20%. All the three vehicles are connected to 6.6kW Level 2 slow chargers.

Figure 3.5: Slow charging characteristics of EV batteries

However, Nissan Leaf begins the charging by drawing 6kW power initially and it gradually increases to 6.3kW till 2 hours 21 minutes. The charging power then gradually reduces to 2kW till 3 hours 39 minutes and drops to zero as SOC approaches 90%. BMW i3 begins the charging by drawing 5.1kW power initially and it gradually increases to 5.4kW till 3 hours 50 minutes. It is then gradually reduced to 1.6kW till 5 hours 55 minutes and then drops to zero kW. Similarly, the Kia Soul EV initially draws the charging power of 4.6kW and it gradually increases to 5.1kW till 3 hours 15 minutes. It starts reducing to 0.6kW till 5 hours 50 minutes and then drops to zero kW.

3.3.6 Parking duration

Parking duration is the time duration for which the EV is parked. This can be differentiated in two categories. First category is the duration of parking at the charging station. This duration is equal to the charging time of each EV. Here, it is assumed that EV will

leave the charging station as soon as its charging event is finished making way to another EV for charging. Such an assumption is practical and valid considering that charging stations are commercial and EVs upon charging would be en route to the destination. This will affect the ‘charging station availability’ parameter.

Another category of parking duration is the parking of EVs at the carpark located nearby offices, shopping malls, food centres and residences. This parameter varies based on different scenarios such as:

- i) The office carpark is occupied during office hours.
- ii) Shopping mall and restaurant carparks are occupied during evening hours.
- iii) Residential carparks are occupied during night hours.

The carpark statistics can be inserted in the system based on the realistic carpark data available for an area under consideration. An example of real-time carpark statistics in a Singapore shopping complex is shown in Figure 3.6, [89]. Figure 3.6 shows that the number of free slots are higher during the time period 12:00AM to 10:00AM. After 10:00AM the number of free slots starts decreasing which coincide with the typical shopping mall opening time. The number of free slots are minimum during 02:00PM and 07:00PM which coincide with the typical lunch and dinner times. The occupancy of parking lot starts decreasing starting at 09:00PM and as the time approaches to 11:00PM which is the typical shopping mall closure time. Similar real-time statistics can be obtained for major shopping malls and residential parking lots in Singapore [89].

Figure 3.6: Carpark occupancy in shopping mall, Singapore

This parameter along with the real data provides a more realistic perspective of EV

usage behaviour. It also aids in a realistic problem formulation process. If an EV is parked for a longer duration, it may prefer to charge in slow charging mode instead of fast charging mode. This could reduce the peak demand as well as enable cost savings through better utilization of off-peak electricity prices. The EVs which show such behavior can also be identified during simulation to study the travel and charging pattern of such EVs.

During the modelling process, the private EVs which charge at the charging stations nearby offices and are en route to office, park themselves at the office car parks. This avoids the unnecessary travelling of private EVs on the roads while running simulation. On the other hand, considering the continuous operation of the commercial EVs, they are not modelled to park themselves in car parks other than charging station.

The privately owned EVs park their EVs at the residential carpark overnight. The private vehicles are set to head towards home after office hours with the average departure time from their present location set at 06:00 PM with standard deviation of 2 hours. Among these EVs, some of the EVs may decide to charge their EV overnight based on the status of other factors. These private EVs are again set to head towards office with the average departure time set at 08:00 AM and standard deviation of 1 hour. This setting ensures that the majority of private vehicles whose destination has been selected as 'office' arrives office during the typical office 09:00 AM to 05:00 PM office shift. While the majority of private EV users with slow on-board charger prefer to charge at residential chargers overnight but the private EVs with fast charging capability may not always prefer charging at home.

The private EVs which have the fast charging capability and insufficient SOC required to reach office may opt for selecting their path via a charging station en route to office. Similarly, some of these private EVs may opt to charge their EV en route to home while departing from office. These decisions are based on the value of factors such as electricity price, charging station availability, urgency factor as well as user experience. This arrangement would avoid the congestion at the charging stations near office locations. These aspects of modelling ensure that EV user behavior is kept similar to

reality.

3.3.7 Critical SOC, (SOC_{Cr})

During the modelling process, the critical SOC i.e. SOC_{Cr} is defined as a new parameter. The SOC_{Cr} refers to the lowest permissible SOC of the EV. It is the SOC required by EV to travel to the nearest charging station from the desired destination of EV. This destination can be the end point EV is currently moving towards or the end point after it resumes on road from carpark or charging station. Below this SOC, the driver will choose to enter the charging station to charge the EV. It is directly affected by range anxiety. The higher SOC_{Cr} usually results in a higher range anxiety. The detailed relation between them is explained in the following parameter.

3.3.8 Range anxiety and battery capacity

The range anxiety is defined as the worry of an EV driver that the battery of EV will run out before EV reaches its destination or in simpler words, it is a fear of becoming stranded without any energy remaining in the EV battery. The battery capacities of EVs affect the range anxiety. Larger battery capacities of EVs enable them to travel longer distances without quickly depleting their batteries. This gives greater assurance to the driver since the chances of quickly running out of energy decreases with an increase in battery capacity. The results in [90] show that there is an inverse relationship between the range anxiety and battery capacity.

The range anxiety parameter is difficult to quantify as it is associated with the feeling of the person. Hence, the new range anxiety index ' γ ' is defined to quantify the range anxiety of EV users. The proposed methodology of calculation of γ uses SOC values of EV. Every EV user is assigned the value of SOC, SOC_{UE}^k , below which they will prefer to get their vehicle charged if the charging station is en route to the destination. This value is the random distribution between 30% to 80% whose mean is decided by the EV user experience.

It is quantified as shown in eqn. 3.16 stated below.

$$\gamma^k = \frac{SOC_{Cr}^k}{SOC_{ev \rightarrow cs}^k} \quad (3.16)$$

where, $SOC_{ev \rightarrow cs}^k$ is the SOC of EV at the instant when EV starts heading towards the charging station while it is on its way to the desired destination.

To explain this, let us consider a scenario where the instantaneous SOC value of EV at a certain moment is 61% and the value of SOC assigned to it which triggers range anxiety to its user is set at 60%. When the instantaneous SOC of this EV will fall below 60% it will keep moving towards the destination until it encounters a charging station along its way. This EV user will then head towards the charging station to get its EV charged before reaching destination. If the EV user heads at the charging station at 50% of its SOC value and its critical SOC is set at 25% then the range anxiety index associated with the EV user will be 0.5.

It should be noted that in eqn 3.16, both the SOC_{Cr} and $SOC_{ev \rightarrow cs}^k$ do not vary at the same time. SOC_{Cr} value is calculated and fixed as soon as the destination of EV is decided and remains the same as long as the destination remains the same. On the other hand, the $SOC_{ev \rightarrow cs}^k$ is calculated at every time instant for all the EVs in the model. When the value of $SOC_{ev \rightarrow cs}^k$ is equal to the SOC_{Cr} , the range anxiety index ' γ ' reaches its highest possible value of 1. The flag is raised for EV to redirect its heading towards the nearest charging station in order to avoid condition of being out of energy/charge. The path trace algorithm used for this process is explained in the later part of this thesis. For the analysis of a range anxiety using range anxiety index, one of the SOC in eqn 3.16 should be kept constant.

The battery capacity of the EV is a key factor in deciding the range anxiety. As a rule of thumb, more battery capacity would lower the range anxiety. As the battery capacity increases the SOC required to cover the same distance decreases. Hence, to cover the same distance to the nearest charging station, lower SOC_{Cr} is required. From eqn. 3.16 and for a constant value of instantaneous SOC of EV, as SOC_{Cr} decreases the range anxiety decreases.

3.3.9 Range anxiety and driver experience

As the driver's experience with the EV grows, it results in a reduction in the overestimation of range requirement [91]. This means that drivers become more experienced in predicting the EV's range in relation to their range requirements thereby leading to a reduction in range anxiety. The authors of [91] also demonstrated that range anxiety has a direct relation to charging behaviour as EV drivers have a tendency to charge very frequently and to charge longer than required. This mindset indirectly leads to higher SOC_{UE}^k levels as drivers charge unnecessarily most of the time.

In the simulation model described in this document, the driver's experience varies with respect to a random distribution between 30% to 80% with among the total number of EVs in the model. The model is formulated in such a way that, the mean and variance of this distribution can be selected in GUI in a scale of 1 to 10 for various test cases based on the data sets and area under consideration of the study. The experience level 10 (highest) defined in the model means that the driver will only search for a charging station when SOC approaches 25%. This percentage has been increased in steps of 5% with each level of decrease in driver experience, up to level 1 (lowest).

3.4 Macro level parameters

These parameters are associated with the group behavior of EVs and their drivers. The presence of EVs at one location will influence the behavior of other EVs present in their vicinity. This aggregated behavior is implemented using the following parameters.

3.4.1 Availability of slots in charging stations

When the EVs arrive at the charging station and before they enter a charging station, the availability of vacant charging slots at the charging station is checked. If there are no vacant slots, the EV will not enter. Thus, it can be seen that EV behaviour is not only affected by its own characteristics but is also dependent on other EVs around it. This affects the SOC_i of the EV. When the slot is not available, the distance to the nearest

charging station and the destination is recalculated. Based on the results with minimum distance and available SOC of EV, the EV user fixes his new destination and starts heading towards it. As a result of this process the charging event gets delayed while the SOC of EV continues to deplete on its way to the new destination. Such an EV when reaches to another charging station with lower SOC_i , takes more energy to reach to desired SOC_f . This also increases the charging duration of that EV as the amount of energy to filled in EV batteries increases. This event further results in occupying the charger for long duration making other EVs to either delay or cancel their charging event. In this way, the cycle triggers a chain reaction across the nearby charging stations. From the perspective of distribution power systems, the charging load which could have appeared at one charging station (effectively on the distribution node to which the charging station is connected) now appears at the other charging station and effectively on another node of the distribution system.

3.4.2 Speed of EVs

The speed of an EV changes according to the vehicles that are around it. It accelerates whenever there are no vehicles ahead of it and decelerates when the speeds of the cars ahead are lower or there is a turning ahead on the road or it encounters a red traffic light. It stops when the speed of the car ahead is zero. Another situation where speed is important is when EVs move backwards, either out of charging stations or parking lots. In such cases, EVs check for other cars to avoid any accidents. Therefore, speed is another factor which largely depends on the interaction of an individual EV with EVs other than itself. It has a direct relationship with the SOC of EVs since the calculation of SOC accounts for the physical distance travelled which involves the speed factor.

The parameter ‘Speed’ is included in the equation for calculating the SOC of EV in eqn 3.3. The speed is calculated using the distance travelled by a vehicle and the time required to travel that distance. Each patch, which is a unit of distance in the simulation platform, is converted into km with respect to the duration of movement of EVs and the

speed setting of EVs in the simulation platform. The speeds of EVs can be observed in real time during simulation. Each EV is assigned the maximum speed limit between 80 km/hr and 90 km/hr based on the random distribution. These speed limits can also be fed using GUI if the actual data is available for the area under consideration and vehicles in it.

3.4.3 Number of EVs

This parameter is critical for deploying EVs. The number of residential and office places as well as the number of charging stations in a particular region can only accommodate a certain number of EVs. Beyond this threshold, charging stations will be overburdened and EVs would start queuing up for empty slots thereby causing further charging delays. Hence, while planning the number of charging stations in any area, it should be adhered that the maximum number of EVs serviced by each charging station is below this threshold value. Several studies are available in literature [92–95] for calculating optimum number of charging stations for a specific area under consideration. Out of the 36 blocks in the model, GUI provides the flexibility to decide the number and location of charging station at any block and study its effect on the charging pattern as well as distribution system overloading. The number of EVs in the model can be changed at any time to change the EV penetration level in the model.

3.4.4 Types of day

EV usage patterns varies with the types of the day of the week. EVs exhibit different behavior on weekdays and weekends. On weekdays, the usage of private EVs is mainly governed by office hours. The EV users travelling to and from to office follow the daily office routine. Their travel pattern as well as the charging pattern can be predicted based on their office shift hours. Though commercial vehicles would continue to operate the entire week in the same manner, their travel patterns i.e. destinations will change. On weekdays, the commercial EVs (in our case, electric taxi) are assumed to ply mostly between offices and residential areas. On weekends, they are assumed to ply between

shopping centres, food centres and residential areas. Office car parks will show less activity during weekends. On the other hand, during weekends, shopping malls and residential car parks show maximum activities [89].

3.4.5 Purpose of travel

This parameter determines the selection of charging stations located en route to the destination. The daily commute to the workplace might result in charging near office charging stations while weekend activities might result in charging either at food centres, shopping malls or residences. In the model, EV is given the choice of selecting its destination based on the type of the day and time of the day. Upon availability of all required parameters, the EV selects the destination among the choices it has. These choices include office, residences, shopping centre, food center and charging stations.

3.4.6 Charging cost

The charging cost of EV at charging stations is another major parameter affecting the behavior of EV users. When the EV is in the commute i.e. moving on the road, the expenditure incurred for travelling each unit distance is calculated at every instant. The total cost of the energy associated with EV is the product of charging cost and amount of energy it used to charge from SOC_i to SOC_f . This energy is then split into the SOC required for travelling to its destination. This gives the cost of running EV per unit degradation of SOC. While selecting the charging station, along with the minimum distance to the charging station, the cost incurred to travel to charging station and the cost incurred to charge up to SOC_f is calculated for all charging stations in the vicinity of moving EV. The EV chooses the charging station associated with the least cost of operation. Moreover, peak hour periods affect the price of charging indirectly. They do not directly alter the price of charging but rather cause a change in the mindset of drivers. During peak hours, drivers tend to disregard the charging price since they are more concerned with getting an empty slot in the charging station. This relationship demonstrates the social aspect of the model as human behaviours are incorporated into it.

3.4.7 Peak Hours

During peak hours, there is a reduced price barrier since people normally disregard the price as getting a charging slot becomes priority. Critical SOC increases as drivers hold less regard for their SOC and prioritize getting a charging slot during peak hours.

For all four types of places i.e. office, mall, residential and food centre, the peak timings can either be typical standard timings as mentioned below and shown in Figure 3.7 or can be manually changed within the simulation platform based on the requirements of any condition. This provides a greater scope to analyze the impact of varying peak timings on the EV charging load demand.

Figure 3.7: Typical probability distribution of EV charging

Typical peak hours used in the model are as follows:

- The standard office peak hours are 8am-10am and 5pm-7pm on weekdays. This is in accordance with the daily office shift timings in Singapore which are usually from 08:30am to 05:30pm. EVs start looking for offices and office carpark once office peak hours begin.
- The standard mall peak hour period is set between 11am-10pm on weekends. Data from [89] shows that there is a sharp decrease in the number of available parking slots in most malls between 11am-2pm and 7pm-10pm. Hence, this period is cho-

sen as the standard peak period for malls. As the price barrier decreases, critical SOC increases and EVs start looking for malls during this period.

- Residential peak hours are set as 10pm-7am on weekdays. Usually, prices for residential charging stations are lower than those of commercial charging stations.
- The peak hour periods for food centres are set between 12pm-2pm and 6pm-8pm on both weekdays and weekends.

3.5 ABM model setup in NetLogo

All macro level and micro level parameters are simulated using the NetLogo software package [80] to simulate real life human decisions by incorporating human behavioral tendencies towards EV charging. It is possible for both micro-level as well as macro-level models to coexist in order to achieve the strengths and eliminate the drawbacks from each of them. The simulation platform developed in this thesis using NetLogo is shown in Figure 3.8. The model consists of a 6X6 grid i.e., 36 blocks. Each block can be selected to function as a residential charging station (RCS), office charging station (OCS), food centre charging station (FCS), shopping mall charging station (MCS), carpark (CP) or residential block ('None'). In addition to these major structures, these blocks are assumed to have several other building structures within it. However, these details are not shown in GUI. The user interface is designed to allow users to select any configuration of blocks and parameters based on statistical data for any region under consideration. This data represents various probabilities and proportions of decision variables in the macro and micro level operation of EVs.

3.5.1 Movement modelling

The basic unit of time in the simulation platform is 'tick'. Each unit of distance or pixel in the GUI is called 'patch'. For the 24 hour simulation model, the NetLogo model performs 28800 ticks. Hence, each EV in the model updates the knowledge of its surrounding then takes decision or updates the decision for every 3 seconds equivalent

Figure 3.8: Overview of EV charging system using NetLogo

real time. With an advancement of each tick the EV moves one step ahead in forward, backward, right or left direction on the next patch. This movement corresponds to the physical distance associated with the speed of EV.

The EVs can accelerate, decelerate or maintain constant speed during their commute. They can even change the lanes, overtake the vehicle in front or turn in any direction at the road junctions. They are allowed to accelerate up to their maximum speed limit set during the system initialization process until there is no car ahead of them and the traffic light is green. The maximum speed limit of all the roads in the network has been kept the same i.e. 90km/hr which is the case with major roads in Singapore. Before overtaking, the EV checks for the presence of cars in the surrounding areas. If another EV is present in the adjacent lane, the overtaking event will not take place. Before turning left, the EVs will check whether there are any cars at opposite direction lane to avoid crashes. The turning of vehicles is modelled at 15km/hr. The model has no boundaries in all four directions. This means that the vehicle travelling at the end of horizontal road in the left direction will appear from the right side of the model on the same road. A similar process happens when the vehicle approaches the boundary in any of the vertical road. With this basic mode of movement set to cars, the choice of direction and speed are

made based on the values of micro and macro level parameters.

3.5.2 EV and charging station modelling

The EVs are the primary agents in the model. Each EV agent in the model is provided with the attributes defined as micro and macro level parameters in the previous sections. During the system initialization process, all the attributes for the EVs are assigned the random value within the prescribed limits and properties of each attribute. When the simulation begin to run, the state of each attribute of each EV gets updates with every tick.

During the initialization process, the number of cars are created based on the number selected in the GUI. These cars are then assigned a car charging capability i.e. fast and slow charging based on the proportion selected in GUI. Each car then gets the brand and battery capacity as well as charging characteristics based on the proportion of each brand out of the total vehicle population selected at the GUI. After this process, the category of the car is assigned randomly among the number of cars created during initialization based on the proportion of private and commercial EV selected in GUI. The commercial EVs are assigned with the fast charging capability. The GUI is created in such a way that the model can be evaluated for the various test conditions. During this process, the cars are randomly placed on the roads and the carpark, and are ready for the movement at the start of the simulation.

Each of the charging stations in the model has 10 chargers and all chargers are capable of Level III DC fast charging and Level II slow charging. Its arrangement is shown in Figure 3.9. The charger provides the charging power to each EV based on its charging rate preference and battery charging characteristics. At the end of each charging event, charging station updates the status of each charger. The charging power supplied at every time step is plotted in the graph for real time monitoring of the loading situation on that charging station.

The roads in the model are based on the LTA Singapore's guidelines- code of practice for traffic control at work zone [96]. The distance between the two traffic lights is kept

800 meters. The simulation study represents the total area of 23.04 sq.km. There are a series of buildings in the blocks between these traffic lights on the both sides of the roads. However, only the charging station, carpark and residential blocks are represented in the GUI for clear understanding of ABM for EV charging. There are 36 blocks of building structures considered in this study as represented in Figure 3.8. The traffic lights change their status after a fixed interval of time. The distance between the traffic lights and the interval of their status change can be varied based on the area under consideration of the study.

Figure 3.9: Charging stations in the GUI in NetLogo platform

3.5.3 Process modelling: Charging process at charging station

It is assumed that the EV begins its charging at the charging station as soon as it gets connected to an available charger and leaves the charging station as soon as its charging event is finished. This assumption is made as the charging station and carpark are totally considered separate entities in this study. The charging stations are exclusively used only for charging and carparks are considered exclusively for parking purpose. The EVs can choose to park at the nearby carpark after finishing their charging event if they prefer it.

The process of charging event is given as follows:

1. The status of each charger is updated at each tick. This will create the report of charger availability status of all the chargers.

Figure 3.10: Load calculation process at EV charging station

2. If the EV is available for charging and the charger is available, the EV gets connected to charger. The initial SOC of EV, brand of EV and battery capacity are taken as an input from the EV system.
3. The charging rate preference and the desired SOC of charging is taken as an input from the EV user. This is possible through the smart apps available with EV manufactures to communicate with the charger and by monitoring the progress of charging. This state-of-art system also alerts the EV user near the end of its charging event so that EV vacates the charging slot as soon as it finishes the charging.
4. Based on the inputs from the EV system and EV users, the charging station calculates the time required for charging each of the EVs up to their desired final SOC and the power required to be fed to each EV.
5. The EVs available for charging are fed with their required power. When the SOC

of EV reaches the desired SOC of that EV, the charging event for that EV is stopped and EV prepares to depart from the charging station. The EVs which have not reached their desired SOC continue to be charged and remain connected to their respective chargers.

6. The status of charger is again updated and it is ready to serve another EV.
7. The process, also shown in Figure 3.10, repeats itself at each tick and the total power required to be served to all chargers is summed up. This power requirement is conveyed to the respective distribution node for further optimal power flow operation.

It is to be noted that during the entire operation, none of the EV is denied the charging and none of the EV gets charged with the compressed rate of charging. The EVs charge at its desired charging rate and desired SOC as long as the charging slot is vacant upon its arrival.

3.5.4 Process modelling: Finding charging station

The search process of charging station does not only depend on the minimum distance but also on the urgency factor as well as the price of electricity at each charging station. These parameters are evaluated simultaneously and the best combination is selected by the EV which fulfills the criteria set by other parameters. This process is initiated by locating the patch on which EV is located. The distance to the all charging stations from the location of the EV is calculated by counting the patches on the roads in terms of the physical distance in kilometers that would lead to these charging stations. The paths are then sorted based on the ascending order of the distance between the current location of the EV and charging stations. This distance is further used in selecting the path to be taken for actual commute of the EV.

3.5.5 Process modelling: Travel path selection and effect of price

The selection of path towards destination depends on the least distance to be travelled but the selection of charging station and hence, the selection of path having that charging station en route to it also depends on the price of electricity at that charging station. When the EV moves ahead with each tick, it incurs some cost. This cost is the running cost of the EV. The charging cost of EV is calculated based on the price of electricity it was charged with, during the last charging event multiplied by the amount of energy supplied to EV (E_{charge}^k). The running cost of the EV per unit distance travelled by the EV is calculated using following equations.

$$C_{charge,i}^k = R_{cs}^n E_{charge}^k \quad (3.17)$$

Where R_{cs}^n is the rate of electricity at the n^{th} charging station. The total worth of energy inside an EV can be calculated as,

$$C_{energy}^k = C_{charge,i}^k SOC_{rise,i}^k + C_{charge,i-1}^k (SOC_{rise,i-1}^k - \sum_{k=0}^N \Delta SOC_{ev}^k) \quad (3.18)$$

In eqn. 3.18, $SOC_{rise,i}^k$ refers to the % rise in SOC of the k^{th} EV at the i^{th} charging event and $SOC_{rise,i-1}^k$ refers to the % rise in SOC of the k^{th} EV at the $(i-1)^{th}$ i.e. previous charging event. $\sum_{k=0}^N \Delta SOC_{ev}^k$ refers to the change of SOC of the EV after its departure from previous i.e. $(i-1)^{th}$ charging event to the latest i.e. i^{th} charging event, Its value is calculated from the eqns. 3.4, 3.5 and 3.6. In other words, it is the sum of cost of the energy required to charge the EV and the cost of the energy remaining in the EV before beginning the charging event at charging station.

Hence it is possible to deduce the cost of running the EV per unit kilometer as follow.

$$C_{run}^k = \frac{C_{energy}^k E^{ev}}{E_{usable}^k} \quad (3.19)$$

Where E^{ev} is calculated from eqn 3.8 and E_{usable}^k is the usable energy of the EV for its

trip duration which corresponds to the usable SOC of the EV and calculated based on the battery capacity of the EV. This usable energy of the EV is calculated as below:

$$E_{usable}^k = (SOC_f^k - SOC_{CR}^k) * B_{ev}^k \quad (3.20)$$

Once the cost of running the EV per unit kilometer distance traveled by the EV is known, the cost of travelling towards the destination is calculated while deciding the path towards the destination. If the EV has enough SOC to reach the destination, the least distance path is selected bypassing all the above equations.

However, if the SOC of EV is not sufficient to reach the destination then the various possible combinations of paths are considered for the EV to reach the destination through the charging station. The cost of travelling to charging station $C_{run \rightarrow cs}^k$, cost of charging EV at the charging station C_{charge}^k and cost of travelling from the charging station to the destination $C_{run \rightarrow dest}^k$ is calculated for each of the possible path leading to the destination. Among the possible combination, the path with a lower cost of operating EV is selected by the EV user. It is represented by the following equations,

$$\arg \min C_{trip}^k, C_{trip}^k = C_{run \rightarrow cs}^k + C_{charge}^k + C_{run \rightarrow dest}^k \quad (3.21)$$

where,

$$C_{run \rightarrow cs}^k = C_{run}^k d_{cs}^k \quad (3.22)$$

$$C_{run \rightarrow dest}^k = C_{run}^k d_{dest}^k \quad (3.23)$$

Based on the path selected by eqn. 3.21, the benchmark time ($T_{benchmark}^k$) in eqn. 3.24 is calculated.

3.5.6 Process modelling: Urgency factor and effect of price

During the development process of the model various sub-parameters are calculated for building the objective functions. The urgency factor is created to study the effect of electricity price and peak price on the charging of EVs. When the EV decides its destination and is ready to depart towards it, the least distance path is calculated to reach that destination. This path also depends on the specific time at which the EV need to reach the destination as well as the time to charge the EV if the current SOC of the EV is not sufficient to reach the destination. Such a path is then calculated through the nearest charging station. After fixing the least distance path, the time required to travel at that place is calculated with respect to average speed of 50 km/hr. This speed can be varied based on the requirement and actual driving conditions if the data is available. 50 km/hr is chosen as a trial average speed based on guidelines from LTA Singapore [85] to implement the urgency factor in the system.

This calculated time is set as a benchmark for the vehicle to reach the destination. As the vehicle starts moving another timer is set to count its trip duration. With the movement of the EV at each time tick, it is compared with the benchmark time and urgency factor is calculated based on the following equation,

$$UF = \frac{T_{est}^k}{T_{benchmark}^k} \quad (3.24)$$

In eqn. 3.24, the T_{est}^k is the time remaining to arrive at the destination and $T_{benchmark}^k$ is the benchmark time required to reach the destination from the moment the EV departs for the destination. It is to be noted that T_{est}^k is updated at each tick based on the speed and location of the EV while $T_{benchmark}^k$ remains the same until the EV reaches its destination.

The EV continues to follow the path towards its destination provided all other parameters such as instantaneous SOC of EV is within the required limit. In this condition, the UF will always be less than '1'. If the UF exceeds the value '1', the EV disregards the price barrier at the charging station and continues to move towards the charging station if it is on its way as a part of its trip towards the destination. As mentioned earlier, the

charging time, if the charging event is occurred before reaching the destination, is also accounted while calculating the benchmark time. Hence, if the EV experiences delay at the charging station due to queuing, the UF tends to exceed value '1' and EV prefers to either end the charging process or reroute the path. The rerouting of the path again follows the same procedure to maintain UF below '1'.

3.5.7 Process modelling: Charging station availability and effect of queuing

When the EV reaches the charging station, it may or may not get the charging slot for its desired mode of charging. The charging station could be fully occupied upon its arrival. In this scenario, the EV has two options to deal with this situation. The first option is to wait in the queue for the charging and begin the charging event as soon as the slot is free for its charging event. Another option is to leave that charging station and search for another charging station.

Whether the EV opts to wait in the queue depends on the value of UF . As the EV waits in the queue, the T_{est}^k is increased with the waiting time. This waiting time is calculated by summing up the least time remaining among all the EVs which are currently charging at the charging station and the estimated time of charging required for the EVs ahead of it in the queue. This process is repeated for each EV in the queue and each EV adds its own waiting and charging time to the next EV waiting at the charging station. This arrangement also prevents the long queues at the charging station as after certain numbers of EVs, it is not feasible for EVs to maintain UF below 1 and they begin searching for another charging station. If the UF exceeds the value of '1', EV chooses not to wait at the queue and searches for the other charging station.

3.5.8 Process modelling: effect of user experience

The EV users with less driving experience can not estimate the range of driving with the remaining SOC of their EV. This mindset leads to higher SOC_{UE}^k levels as drivers

charge unnecessarily most of the time. SOC_{UE}^k is the SOC below which EV drivers tend to charge at the charging station and plans their trip according to it.

In the simulation model described in this document, the driver's experience varies with respect to a random distribution between 25% to 70% among the total number of EVs in the model. The model is formulated in such a way that the mean and variance of this distribution can be selected in GUI in a scale of 1 to 10 for various test cases based on the data and area under consideration of the study. The experience level 10 (highest) defined in the model means that the driver will only search for a charging station when SOC_{UE}^k approaches 25%. This percentage has been increased in steps of 5% with each level of decrease in driver experience, up to level 1 (lowest). Thus the SOC_{UE}^k for the user experience of level 1 is set at 70%.

To simulate the tendency of the EV users associated with their user experience, the instantaneous SOC of the EV is checked with the SOC_{UE}^k when the EV is deciding the path towards its destination. If the instantaneous SOC of EV falls below SOC_{UE}^k during the commute, EV continues to follow its path and reaches the destination. The process of finding the charging station en route to the next destination is implemented at the departure time.

3.5.9 Process modelling: Path selection - office-carpark-residence

This process is applicable to the private EV category. The private EVs which are assumed to mostly commute between office and residential places during the weeks are set to depart towards office from the residence in the morning office hours. These EVs depart for the residences at the end of office hours. If the SOC of the EV is not sufficient to reach the destination, the EVs decide their path towards office/residences en route to a charging station. However, it is taken into consideration that these categories of EVs remain parked at the office carpark during office hours when their destination is set as office and they remain parked at residential carparks the entire night after they arrive at the residential places until the beginning of the next office hours. This assumption helps in avoiding unnecessary roaming of private EVs in the model during office and night

hours and helps in creating real life scenarios of EV usage.

3.5.10 Process modelling: Path selection - Electric Taxi

The commercial EVs i.e. electric taxis which are assumed to mostly commute between pick up and drop off locations exhibit entirely different dynamics compared to private EVs. The pick up and drop off location is selected as a random patch in the model. When the pick up location is selected and the taxi is not at that location, that pick up location is set a destination for the EV and the path to reach that destination is selected. The taxi then departs from the destination. After its arrival at the drop off location, the remaining SOC of the EV is checked. If this SOC is lesser than or equal to the SOC_{CR}^k of the EV then the charging station is selected based on the various criteria defined earlier and the taxi moves towards the charging station. The process of commute between pick up and drop off points continues once the taxi is charged to the desired SOC_f^k .

It is to be noted that these categories of EVs are modelled to operate the entire day. In other words, they do not park themselves in car parks. Also, electric taxis are assigned with a fast charging capability with a consideration that they need to keep charging time minimum in order to operate for more time. Also, the process of path selection for commercial EVs is unlike the process of path selection for private EVs where a charging station could be chosen to be en route to the destination. In the path selection process of the taxis, the charging station is never selected en route to any pick up and drop off location. Taxis are set to move towards charging station only after the commute to drop off location is complete. This is a practical assumption that the taxis should not charge during their commute as it will increase the time to commute and is not favourable in the taxi business.

3.5.11 Operation of all processes

Figure 3.11 shows the various processes, their inter dependency and flow of operation for the ABM. It is to be noted that each of the processes depends on the inter dependency of the parameters shown in Figure 3.1. The ‘model initialization’ stage consists of the

setup of EVs, charging stations and environment setup as stated in details in section 3.5. The operation planning phase consists of various calculation processes such as running cost calculation, charging station selection, path selection, travel duration calculation and charging station operation as explained in section 3.5.

When the entire model setup is done according to the data and area under consideration, the system initializes all the parameters. When the model begins to run, each process operates independently based on the parameters available at each EV. Some of these processes are interdependent and form the cycles of operation during the simulation period. This is the execution stage of ABM as shown in Figure 3.11. After each tick, all the parameters of each EV and charging station are updated and the feedback is provided to all the processes. This last stage of feedback acts as further inputs to sustain the operation of the model and the model continues to run until the desired time of operation.

The selection of some of the parameters in the NetLogo is done using the GUI as

Figure 3.11: Operation of ABM in NeLogo

residential	carpark	none	none	none	none
setting-7	setting-8	setting-9	setting-10	setting-11	setting-12
carpark	carpark	none	none	none	none
setting-13	setting-14	setting-15	setting-16	setting-17	setting-18
none	carpark	office	foodcentre	carpark	none
setting-19	setting-20	setting-21	setting-22	setting-23	setting-24
none	carpark	mall	office	carpark	none
setting-25	setting-26	setting-27	setting-28	setting-29	setting-30
none	none	none	none	carpark	carpark
setting-31	setting-32	setting-33	setting-34	setting-35	setting-36
none	none	none	none	carpark	residential

price-of-charging-1-\$/kWh	0.25	office-peak-period-morning	11	hours	12
price-of-charging-2-\$/kWh	0.25	mall-peak-period-morning	11	minutes	0
price-of-charging-3-\$/kWh	0.25	residential-peak-period-morning	9	period	am
price-of-charging-4-\$/kWh	0.25	foodcentre-peak-period-morning	11	type-of-day	weekday
price-of-charging-5-\$/kWh	0.25	office-peak-period-afternoon	2	☒ On ☐ Off standard	
price-of-charging-6-\$/kWh	0.25	mall-peak-period-afternoon	4	Setup ⁵	Go (24 hr) ²
price-of-charging-7-\$/kWh	0.25	residential-peak-period-afternoon	5	Go ^G	
price-of-charging-8-\$/kWh	0.25	foodcentre-peak-period-afternoon	6		
num-of-cars	120	office-peak-period-night	7		
proportion-of-BMWi3	10	mall-peak-period-night	12		
proportion-of-NissanLeaf	10	residential-peak-period-night	11		
proportion-of-KiaSoulEV	10	foodcentre-peak-period-night	12		
proportion-of-private-vehicles-green	7				
proportion-of-commercial-vehicles-blue	3				
max-driver-experience	5				
prob-of-normal-over-fast-charge	5				

Figure 3.12: GUI in NetLogo platform for parameter selection

shown in Figure 3.12. This gives flexibility to generate case studies for studying the effect of variation in a particular parameter on the charging load at each charging station.

While the simulation model is running, real-time data of any EV can be observed to track its brand, battery capacity, type of charging, charging power level, travel pattern, battery SOC levels, total distance travelled after each charging event, historical charging data such as the number of previous charging events and number of previous visits to

Figure 3.13: Realtime monitoring of EV parameters in NetLogo platform

a particular charging station. These details are shown in figure 3.13. In Figure 3.13, the blue colored vehicle represents the commercial EV and the yellow colored vehicle represents the private EV.

3.6 Results and sensitivity analysis

The proposed model is simulated for several days over a 24 hour time period frames from 12:00 midnight to 11:59pm for various cases. The model is first allowed to run for several hours for all the agents to follow the routine. After the agents started following the charging process routine and daily travel commute routine, the results were extracted and plotted as shown in Figure 3.14. This procedure is used to eliminate errors arising from the initialization of system parameters. The total power demand due to the charging process of all EVs considering all charging stations in the system is shown in Plot(I) of Figure 3.14. The overall charging demand from office charging stations is shown in Plot(II) whereas Plot(III) of Figure 3.14 shows the charging demand from residential charging stations.

Electricity prices are considered to be the same for all charging stations during this case of simulation. The 120 EVs are considered in the model. 70% of them belong to the private EV category and 30% of them belong to the commercial EV category. The driver experience is set at level 7. This will distribute the SOC_{UE}^k with the mean of 40% and standard deviation of 3 i.e. between 25% and 45%. One half of the total EVs in the model is randomly assigned with the fast charging capacity and remaining EVs are assigned with the slow charging capacity. The typical weekday is chosen for this case to observe the private EV user operation around office charging stations and residential charging stations. All these parameters along with the peak times for each of the charging station according to its type are summarized in Table 3.3.

Table 3.3: System parameters

Electricity price	\$0.20 / kWh	Charging station peak hours	
Number of EVs	120	Office	$\mu = 9, \sigma = 2$ (Morning) $\mu=17, \sigma = 2$ (Evening)
Private EVs	70%	Mall	$\mu = 20, \sigma = 3$
Commercial EVs	30%	Food center	$\mu = 12, \sigma = 2$ (Morning) $\mu=20, \sigma = 2$ (Evening)
Driver experience	(Level 7) $\mu = 7, \sigma = 3$	Residential	$\mu = 2, \sigma = 4$
Fast charging EVs	50% of total EVs	Type of Day	Weekday

Following are the observations made from Figure 3.14.

Figure 3.14: EV charging load- Plot(I) Total charging load, Plot(II) Charging load near offices, Plot(III) Food centre charging load, Plot(IV) Residential charging load 1, Plot(V) Residential charging load 2

1. The total charging load at the charging stations shows the peaks distributed throughout the day. These peaks occur due to the connection of EVs with the fast charging capacity.
2. The variation of total charging load shows the peaks during midnight between 02:00 am and 03:30 am, during morning from 09:00 am to 12:00 pm and during night between 09:00 pm and 11:30 pm. This occurrence of peaks in these times is similar to a typical load behaviour exhibited in the power system.
3. The charging load at the OCS shows the peak demand beginning from 08:00 pm and sustained with a small reduction in demand till 12:00 pm. From 12:00 pm the charging load decreases gradually. The charging activity again shows some peaks around the 05:30 pm but sustained only for short duration of 1 hour. This is justified as EVs going to office charging station have been charged in the daytime an evident from the increased charging activity during that time.
4. The FCS shows the peak demand distributed during the afternoon between 01:00 pm and 05:30 pm. The prominent peak appears between 01:00 pm and 02:00 pm. The peaks show up again for a short duration between 07:00 pm to 09:00 pm. This charging station is mostly used by the commercial EV category with flexible meal times as well as the users in the private EV category.
5. The RCS1 shows that the charging loads have peak between 08:00pm and 03:30 am and RCS2 shows the peak between 09:00pm and 12:00 pm. This verifies the fact that a considerable amount of private EV users prefer to charge near their residences during the night time due to their slow charging capacity.
6. The intermittent peaks arising in the charging load demand at RCS1 and RCS2 during the daytime could be the result of commercial EVs which were charged there after dropping off the passenger nearby.
7. The charging load near offices is higher during office hours since EVs are charged at residential charging stations during the night.
8. Residential EV charging starts after office hours at approximately 08:00 pm and

decreases close to the beginning of office hours on the next day i.e. at 08:00 am.

The key inference from all of the above simulation results is that when human behaviour is included while predicting EV charging demand, the peak demand occurs based on daily activities of users. It is clearly highlighted from the Figure 3.14 that the ABM approach for determining the EV charging demand generates results which are close to reality.

To study the effect of variation of various parameters on the EV charging demand at individual charging stations as well as on the total charging demand of the system, different test scenarios are generated. These test scenarios leads to the sensitivity analysis of these parameters. These test scenarios are as follows.

3.6.1 Effect of variation in proportion of EV categories

As discussed earlier, the commercial EVs are fitted with the fast charging capacity. An increase in proportion of commercial EVs would definitely increase the power requirement at each charging station thereby increasing the total charging load of the system. By keeping all the other parameters mentioned in Table 3.3 and changing only the proportion of commercial EVs to 80% and private EVs to 20% of the total number of EVs in the model, we get the total charging load of the system as shown in Figure 3.15.

Figure 3.15: Total charging load for 80% Commercial EVs and 20% Private EVs

Figure 3.16: Effect of variation in proportion of commercial EVs

It is clearly seen in Figure 3.15 that the number of peaks in the charging load has increased considerably compared to the results of Plot (I) of Figure 3.14. The average total charging load of the day has increased from 97 kW to 148 kW with the 10% increase in the proportion of commercial charging load. This is 52.5% increase in the load requirement due to addition of EVs capable of fast charging.

To further understand the effect of variation of the proportion of commercial and private category of EVs on the load requirement of the charging stations, the proportion of commercial EVs are increased from 0% to 100% in the steps of 10%. The rest of parameters are kept same as mentioned in Table 3.3. The case of 0% commercial EVs corresponds to the system with only private EV users operating in the region. This situation is similar to early adoption of EVs. The average EV charging load at the EV charging station in this case was observed to be 43.51 kW. Case of 100% commercial EVs corresponds to the situation of high EV penetration and wide spread EV adoption. The average EV charging load at the EV charging station in this case was observed at 72.14 kW. This is the 65.8% increase from the case of 0% commercial EVs. The variation in average charging load for this test case is shown in Figure 3.16. From

the Figure 3.16, it is observed that the daily average charging load demand also increases with an increase in the proportion of commercial EVs in the system. The percentage increase in EV charging load is significant for a single charging station. This is also quite natural since commercial EVs are assumed to operate 24 hours a day in shifts as opposed to private EVs which operate only for a limited number of hours every day. The average energy consumed by commercial EVs is therefore higher when compared with private EVs.

3.6.2 Effect of variation in user experience

As discussed earlier, the variation in user experience is associated with the range anxiety of EV users. It is more related to the private EV users compared to commercial EV users. This is due to the greater driving experience of commercial EV drivers.

Figure 3.17: Total charging load for least EV driver experience

To see the effect of variation in user experience, the proportion of commercial EV users is made 20% and the proportion of private users is made 80%. The user experience is changed to least i.e. 1. This means that the EV users will show a high range of anxiety. The rest of parameters are kept same as mentioned in Table 3.3. The results obtained for this test case is shown in Figure 3.17. After comparing the result with the total charging load in Figure 3.14, it is clearly visible that the load in Figure 3.17 shows many sharp peaks distributed throughout the day. The occurrences of peaks is continued during the

Figure 3.18: Effect of variation in user experience of EV users

night period which shows that even commercial EV users with least EV user experience levels prefer to charge their EV frequently.

In order to study the effect of variation in user experience on the total charging load of the system in details, the user experience is varied from level 1 to level 10. The level 1 user experience corresponds to the SOC_{UE}^k of 25% and level 10 corresponds to the SOC_{UE}^k of 70%. With the each step increase in user experience level, the SOC_{UE}^k value increases by 5%. The average daily charging load of the entire system is obtained for all these cases and plotted as shown in Figure 3.18.

The average charging load at the least user experience is 81.75 kW while for the highest user experience it is 57.29 kW. This is the reduction in average daily power requirement by 24.46 kW. In other words, increase in the user experience in these test cases resulted in the reduction of nearly 30%. From the results of this case, it is clearly observed that the daily average charging load demand decreases when driver experience increases since EV users are more aware about their vehicle range and do not resort to panic charging before battery SOC drops to its critical level.

This analysis suggest the need of educating EV users about driving range estimation of their EVs. The analysis recommends the need of developing tools to simplify

range calculation for EV users to reduce their range anxiety. These tools among others include range estimator, real-time battery SOC monitor and smart communication interface between the charging station network and EV.

3.6.3 Effect of variation in type of charging: DC fast & Level II slow

The proportion of EVs capable of fast charging would certainly increase the power requirement from the charging station. This is due to a higher charging power requirement of each EV. To verify this assumption, the proportion of fast charging EVs is increased from 0% to 100%. The rest of parameters are kept the same as mentioned in Table 3.3. The results are obtained for each test case with increasing proportion of fast charging station by 10% for each case. The daily average charging load of the entire system shown in Figure 3.19 shows the rising trend. The average daily load when all the EVs are only capable of using level II charging facility is 79.19 kW while with the 100% DC fast charging capability it reaches 108.18 kW. This shows that with the complete transformation of the EV fleet from level II slow charging capability to the DC fast charging capability would result in 26.8% rise in the total charging load of the system. This

Figure 3.19: Effect of variation in proportion of fast charging EVs

verifies the assumption of the increase in charging load with increase in fast charging capability of EVs.

This analysis opens up the challenges to the system operator to make the system ready to absorb the high power charging EV fleet and facilitates the investigation of new congestion alleviation techniques for optimal power flow in the system.

3.6.4 Effect of variation in electricity price

As discussed in previous sections about the dependency of path selection based on electricity price, the EV users will decide to charge at the charging station based on the minimum value obtained using eqn. 3.21 and 3.24. To assess the impact of variation in pricing on charging load at various charging stations, electricity prices are varied as shown in Figure 3.20 for different charging stations.

The electricity price at the RCS1 is raised to \$0.30/kWh from 09:00 pm to 07:00 am. The electricity price at the OCS is raised to \$0.30/kWh from 08:00 am to 10:00 pm during morning and from 04:00 pm to 06:00 pm during evening. The electricity price during other hours of RCS and OCS as well as during all the operating hours of FCS

Figure 3.20: Electricity price profiles of charging stations

and RCS2 are kept at \$0.20/kWh. The rest of parameters are kept same as mentioned in Table 3.3. A localized peak price is imposed during the hours when the respective charging stations encounter peak charging demand. For example, from Figure 3.20, it is evident that the OCS imposes peak prices during times of maximum load demand during morning and evening hours. The study, while not necessarily fully consistent with electricity market principles, provides insights into how EV owners could behave when localized peak prices are charged and how it could impact their decisions regarding preferred charging locations and charging times.

Another test case is also created by keeping the electricity price at all charging stations the same during the entire day. Both test cases are run for the period of 24 hours each and the results of charging load at RCS1 and OCS before and after the change of electricity price are plotted as shown in Figure 3.21 and 3.22.

Figure 3.21: Effect of rise in price during peak hours at RCS

Figure 3.21 shows the charging power requirement at RCS with and without peak hour pricing. It can be observed that a significant portion of the charging load at RCS has been shifted to off-peak hours. The inference from this observation is that EV users prefer not to charge during high price hours and prefer to charge their EVs during off-peak hours. It can also be observed that the average peak power has reduced from 33.51 kW to 20.98 kW. Hence, the two-tier pricing has a considerable impact on the behaviour of EV drivers in RCS.

Similarly from Figure 3.22, a significant reduction in the peak power requirement

at OCS can be observed during afternoon office hours from 11:30 am to 06:00 pm and the charging demand is distributed more uniformly than without peak power pricing. Furthermore, a significant reduction in average peak power from 44.69 kW to 29.68 kW can be observed from Figure 3.22.

Figure 3.22: Effect of rise in price during peak hours at OCS

It may be inferred that the EV charging demand is influenced by electricity prices and EV users prefer to charge at charging stations with lower prices. This analysis not only helps in identifying the loading requirements of charging stations but also has other applications. For example, based on the predicted behaviour, appropriate demand response strategies could be designed.

Another application of this study is in the sizing of stationary energy storage systems (ESS) which could provide support to the grid in case of overloading caused by a particular charging station. Each of these applications is interesting in its own right and merits a thorough investigation which is demonstrated in the later section of this thesis.

3.6.5 Summary of sensitivity analysis

The major socio-economic parameters identified from the literature are varied from 0% to 100% in the steps of 5% to 10% to study their effect on EV charging behavior at various charging station locations. Hence, the sensitivity analysis in this study specifies the requirements of accuracy of these parameters with the minimum deviation of 5% to 10% depending on case to case basis. From the above mentioned sections 3.6.1 to 3.6.4,

the effect of variation of major socio-economic parameters on the EV charging load can be summarized as follows:

- The presence of commercial EVs significantly affects the EV charging load but in varied proportion. The average charging load during the absence of commercial EVs was found to be 43.51 kW. When the entire EV fleet is replaced with commercial category of EVs, the average load at the charging station increased to 72.14 kW. This is a 65.8% increase in the average charging power requirement due to the replacement of privately owned EVs by commercial EVs. It is also observed from Figure 3.16 the increase in charging power requirement is not significant with every 10% increase in the commercial category of EVs. The charging power increases by around 6% with each 20% increase in commercial category of EVs.

This analysis signifies that any EV charging station which is designed to the present number of commercial EVs can accommodate 20% more EV penetration without significantly impacting peak demand of EV charging stations.

- The driving experience of the EV user determines its range anxiety and hence the charging frequency and behavior. With each step increase in user experience level, the SOC_{UE}^k value increases by 5%. From Figure 3.18, it is observed that the average charging load at the least user experience is 81.75 kW while for the highest user experience it is 57.29 kW. This signifies that increase in the user experience results in the load reduction of 24.46kW i.e. nearly 30%. It is also to be noted that the reduction of the charging power requirement is not significant with mere 5% increase in user experience. The charging power reduces approximately by 3 kW with every 10% increase in user experience.

This analysis signifies that any EV charging station designed to the present average user experience, the peak charging demand would reduce with the time and the charging station capacity would be able to serve during the increase in power demand due to change in number of EVs.

- The proportion of fast charging capability of EV increases the charging power requirement of the charging stations. Figure 3.19 shows that the average charging

power required when all the EVs are only capable of using the level II charging facility is 79.19 kW while with the 100% DC fast charging capability it reaches 108.18 kW. This shows that with the complete transformation of the EV fleet from the level II slow charging capability to the DC fast charging capability would result in 26.8% rise in the charging power requirement of the charging station. Again, it can be observed that the power demand increases significantly with each 20% increase in fast charging EV numbers.

This analysis signifies that if 20% of the slow charging EVs are replaced or modified with the DC fast charging capability, the existing EV charging infrastructure would be able to accommodate their charging power requirement without a significant increase in peak charging demand.

- The electricity price for the charging is the major economic factor influencing the EV adoption rate. Hence the reaction of the EV users to the variation in the charging price needs a careful evaluation. The sensitivity analysis for the charging price shows that the average load at both RCS and OCS reduces by 37.39% and 33.58% respectively when the peak pricing is enabled. Further, more users prefer to charge at the RCS during low price hours to reduce the cost of charging at OCS during high price hours. This is evident from Figures [3.21](#) and [3.22](#).

This analysis signifies that the EV charging load is flexible and highly dependent on the variation in electricity price. The price of charging can play a significant role in reducing the peak charging power requirements of charging stations by enabling the shift in charging times at these charging stations.

3.7 Applications and extensions of ABM results

With the ability to predict the behavior of the EV users with the variation of one or more parameters simultaneously, the ABM of EV charging load opens up the scope for extending its results for various system studies. These studies include the energy storage sizing for the individual charging station, congestion analysis of the distribution

system and the demand response based optimal energy management of a single charging station based on economic considerations. These possible extensions of the results are demonstrated briefly in this section.

3.7.1 Application in ESS sizing

Here, the case of ESS sizing is presented as an application of the extended results obtained from the simulation platform.

For the commercial charging stations, the charging time and waiting time are both required to be minimum. This can be achieved by using ESS for EV charging stations. This will serve as a buffer between the grid and the EVs. Also, EVs should not be kept waiting for long hours to get charged. Another advantage of deploying ESS between the grid and EVs is to utilize variations in the electricity prices of the wholesale electricity market by optimizing the cost-effectiveness of the ESS for this application. This aspect of ESS is explained in details in Chapter 4.

For this application study, a single office charging station is considered. The charging station is assumed to have equipped with the rooftop PV. The charging station is also equipped with the ESS whose size needs to be determined using the analysis below.

The PV system in this case-study is of 75 kW_{peak} rated capacity and is selected based on the guidelines issued by Singapore's Land Transport Authority (LTA) for an area for 20 parking lots [97]. Figures 3.23 and 3.24 show box-plots of the energy required at the OCS and energy generated by the PV system respectively. It may be noted that Figure 3.23 is obtained from NetLogo simulations performed over a period of 24 hours. Figure 3.23 represents the charging load of OCS with the peak power demand of 78 kW.

The power output from a PV system at the j^{th} interval in a given day is calculated as follows:

$$P_j^1 = P_{pv,peak} \cdot \frac{SI_j}{1000} \cdot [1 - \beta_{pv}(T_{amb,j} - T_{amb,rated})] \quad (3.25)$$

Figure 3.23: Box-plot for EV Load at OCS

$$P_j = \eta_{conv} \cdot \delta_{PV} \cdot \eta_{MPPT} \cdot P_j^1 \quad (3.26)$$

where SI_j is the measured solar irradiance during the j^{th} time interval; β_{pv} is the temperature coefficient for the module's efficiency; $T_{amb,j}$ is the measured ambient temperature during the j^{th} time interval; $T_{amb,rated}$ is rated ambient temperature ($30^\circ C$) and $P_{pv,peak}$ is the maximum power generated under standard test conditions [98]. P_j^1 is the power output from the solar PV system during the j^{th} interval before considering power conversion efficiency and P_j is the power output after considering power conversion efficiency. η_{conv} , δ_{PV} and η_{MPPT} represent the efficiency of the converter, de-rating factor for PV panels and efficiency of maximum power point tracking (MPPT) respectively. The value of $\eta_{conv} \cdot \delta_{PV} \cdot \eta_{MPPT}$ is considered to be 0.85 [98].

Figure 3.24 is obtained from real solar irradiance data available in [99] by using the above formulation.

The objective chosen for sizing the energy storage system is to avoid a condition where the solar PV generation is higher than the total EV load and the ESS capacity is not sufficient to store the surplus energy. This is a realistic condition wherein the charging station operators would prefer some flexibility to charge/discharge the ESS based on market conditions. The ESS designed for such conditions will cater for worst

Figure 3.24: Box-plot for PV output at OCS

Figure 3.25: Energy Storage requirement at OCS

case scenarios. However, the operation can be optimized using methods such as the one proposed and explained in Chapter 4. With the given load and available PV power, the size of the ESS is given by the following equation:

$$Size_{ESS} = \sum_{i=1}^{24} E_{PV,j}^{max} - E_{EV,j}^{min}, \forall E_{PV,j}^{max} - E_{EV,j}^{min} > 0 \quad (3.27)$$

For this application, the ESS capacity is given by the area under the curve shown in Figure 3.25 for $E_{PV,j}^{max} - E_{EV,j}^{min} > 0$ and it is calculated to be 419 kWh.

It is to be noted that, a sample case of ESS sizing for OCS is shown above. Similar ESS sizing can be achieved for other charging stations and with the use of more state-

Figure 3.26: Modified IEEE 14 bus power system having EV charging stations

of-art methods.

3.7.2 Application in congestion analysis

In this section, the agent environment is mapped into an exemplar electrical grid to demonstrate the practical applicability of the charging demand prediction model developed in this thesis. A modified IEEE 14-bus system is chosen as the exemplar electrical grid in this study as shown in Figure 3.26.

In this application study, the distance between the traffic lights has been doubled to 1600 meters. Hence, the total system now represents the area of 92.16 sq.km. It is assumed that residential charging stations are located at buses 2 and 9 which are located approximately 11km apart from each other. The residential charging station at bus 2

has the peak charging load of 236.13 kW while the one at bus 9 has 326.52 kW peak charging load. The office charging station is located at bus 3 which is approximately 5km from bus 2 and 7.5km from bus 9 and has the peak charging load of 232.15 kW. The food centre charging station is located at bus 4 with the peak charging load 284.97 kW. It is located near to bus 3 with an approximate distance of 2km. This structure is adopted from Figure 3.8 superimposed on the modified IEEE 14 bus system shown in Figure 3.26.

It is assumed that EV charging loads constitute 5.2% of the total system load demand [100]. The charging stations are located at buses which have a relatively larger connected load. To make the network more suitable to be used in the current spacial configuration of the grid, the line resistance values were increased to 5 times the standard p.u. values provided in the MATPOWER [101] case files. The line reactance p.u. values were left unchanged. These values of the line parameters are mentioned in Table 3.4.

Table 3.4: Modified IEEE 14 bus power system line parameters

Line number	From bus	To bus	Resistance (p.u.)	Reactance (p.u.)
1	1	2	0.0969	0.05917
2	1	5	0.27015	0.22304
3	2	3	0.23495	0.19797
4	2	4	0.29055	0.17632
5	2	5	0.28475	0.17388
6	3	4	0.33505	0.17103
7	4	5	0.06675	0.04211
8	4	7	0	0.20912
9	4	9	0	0.55618
10	5	6	0	0.25202
11	6	11	0.4749	0.1989
12	6	12	0.61455	0.25581
13	6	13	0.33075	0.13027
14	7	8	0	0.17615
15	7	9	0	0.11001
16	9	10	0.15905	0.0845
17	9	14	0.63555	0.27038
18	10	11	0.41025	0.19207
19	12	13	1.1046	0.19988
20	13	14	0.85465	0.34802

The total system load was divided among the buses in the same ratio as the original

MATPOWER case file. The modified 14-bus network is operated as a microgrid with some embedded generation present in the microgrid as well. It is assumed that bus 1 has a point of common coupling (PCC) with the main utility grid and has a maximum real power exchange capacity of 1MW. Buses 2, 3, 4 and 9 have solar PV power plants with capacities of 150 kW, 75 kW, 75 kW and 150 kW respectively. Buses 3 and 4 have energy storage systems with capacities of 420 kW and 300 kW respectively. These sizes are determined using the process defined in the previous ESS sizing section 3.7.1. Diesel generators of 3 MW capacity are placed at buses 3 and 8 respectively. The base value for the simulation was considered as 8000 kVA. The parameters of the diesel generators are provided in Table 3.5 [102]. In Table 3.5, a, b and c are fuel cost curve coefficients while P_{min} and P_{max} are minimum and maximum powers produced by the diesel generator respectively. Hence, it is to be noted that the modified IEEE 14-bus system used this study represents the scale-down medium voltage system for a spacial resolution of 92.16 sq. km area.

Table 3.5: Diesel Generator Parameters

Gen	Bus	a (\$)	b (\$/kW)	c (\$/kW ²)	P_{min} (kW)	P_{max} (kW)
1	3	80	0.03	0.000001	100	3000
2	8	200	0.06	0.000002	100	3000

The The MATPOWER package is used in MATLAB to solve the optimal power flow (OPF) problem for this network. Charging load demands generated by the agents in NetLogo are provided as inputs for solving the OPF problem. The OPF problem was solved for different kinds of system loads ranging from high charging load to low charging load. For the network configuration mentioned in the previous paragraph, it was observed that the OPF converged without any difficulty. Moreover, no voltage overloads were observed at any of the buses. The voltage, generation and load details of all 14 buses are summarized in Table 3.6.

The network configuration especially the placement of generators was however finalized after extensive trial and error attempts using MATPOWER. Techniques such as the Jump and Shift method described in [102] may be used to combine the schedul-

ing (unit commitment) and OPF problems to verify the feasibility of scheduling results. Similar efforts can be found in literature in addressing congestion alleviation using the valley-filling algorithms [103].

Table 3.6: Results obtained from modified IEEE 14 bus test case

Bus #	Voltage		Generation		Load	
	Mag (pu)	Ang (deg)	P (MW)	Q (MVar)	P (MW)	Q (MVar)
1	1.056	-11.951	3000.00	-368.51	0.00	0.00
2	1.036	-12.742	-	-	471.87	486.57
3	1.038	-12.720	2792.78	468.28	2048.40	727.95
4	1.011	-13.627	-	-	1039.42	-149.42
5	1.012	-13.312	-	-	165.26	61.30
6	1.060	-15.050	-	-	243.55	287.35
7	1.040	-14.358	-	-	0.00	0.00
8	1.060	-14.358	0.00	952.34	0.00	0.00
9	1.032	-14.743	-	-	641.48	635.99
10	1.030	-14.653	-	-	195.71	222.21
11	1.041	-14.773	-	-	76.11	68.96
12	1.044	-14.966	-	-	132.65	61.30
13	1.038	-14.788	-	-	293.56	222.21
14	1.016	-14.621	-	-	324.00	191.56
Total			5792.78	1052.12	5632.00	2816.00

3.8 Conclusions

This chapter explains the ABM process in details. The ABM technique aims to find explanatory insights through the assessment of the collective behaviour of agents in their natural environment. It does not solve engineering problems by designing agents in a deliberate manner. The behaviours of agents in reaction to the various stimuli help in the detailed analysis of the effect of these stimuli on their collective behavior. This analysis can further help in policy making of EV adoption based on regional demographics.

The microscopic parameters are responsible for independent decisions of the EV users and they are identified as follows: category of EV, initial SOC, final SOC, mode of charging, charging time, parking duration, critical SOC, range anxiety, battery capacity and driver experience. The macroscopic parameters are responsible for the collective behavior of the EV users and they are identified as follows: availability of charging

stations, speed of EV, number of EVs, i.e. EV penetration level in the region, type of the day, purpose of travel, charging cost and peak hours for traffic congestion as well as peak electricity pricing. These parameters influence each other and provide a complex interdependent ABM for EV charging. These inter-dependencies are captured in the process modellings of urgency factor, queuing, user experience and charging station path finding and tracing algorithms for private EVs and electric taxis.

The sensitivity analysis is performed on the major socio-economic factors among all. The sensitivity analysis based on a proportion of commercial category vehicles signifies that EV charging stations capable of fully accommodating present charging requirements can accommodate 20% more EV penetration without significantly impacting the peak demand of the EV charging station. This sensitivity analysis of user experience suggests that as EV user become more experienced, the frequent charging events are lowered resulting in lower charging demand. The power demand can be reduced up to 30% if the drivers are well aware about driving range of the EV battery. This highlights the need of more accurate battery SOC estimation techniques to reduce range anxiety of EV users. The analysis also shows that if 20% of the slow charging capable EVs are replaced or modified with the DC fast charging capability, the existing EV charging infrastructure would be able to accommodate their charging power requirement without significant increase in peak charging demand. It has been observed that the electricity price plays a major role in deciding the preference of charging station among EV users. With implementation of a higher peak hour pricing, 33.58% of EV charging load reduction has been observed at OCS.

With the ability to predict the behavior of the EV users with the variation of one or more factors simultaneously, the ABM of EV charging load opens up the scope for extending its results for various system studies. ESS sizing is presented in this chapter as one of the extensions of the ABM for EV charging load. The calculations show that for OCS with on-site PV charging capacity of 75 kW peak and having peak charging demand of 78 kW, 419kWh of ESS is required to support the base load of EV charging. ESS sizing technique is used for several other charging stations and placed in the

modified IEEE-14 bus system to study the congestion analysis of the network. For the spacial resolution of 92.16 sq. km, four charging stations with the peak charging load requirement of 236.13 kW, 326.52 kW, 232.15 kW and 284.97 kW were placed in the network. Buses 2, 3, 4 and 9 were equipped with solar PV power plants with capacities of 150 kW, 75 kW, 75 kW and 150 kW respectively. Buses 3 and 4 were having energy storage systems with capacities of 420 kW and 300 kW respectively. The OPF was run using this configuration and voltages were found to be within limits on all buses. This scale-down network shows the capability of utilizing load profiles generated using the ABM process in chapter 3.

To further analyse the operation of a single commercial EV charging station, the results from the ABM process in chapter 3 are used in the hybrid optimization algorithm which is defined and explained in chapter 4.

Chapter 4

Economic Analysis of PV Integrated Charging Stations with On-Site ESS

For the commercial EV users, the charging time is the significant factor as more the time EV is out-of-service during charging less the earnings of the EV users. From the perspective of commercial charging station this time constraint depends on the total charging power available at the charging station. Hence, to cater these commercial EV users, commercial charging stations must be equipped with supplementary energy resources to always fulfill the charging demands. On-site ESS and on-site PV are the most widely used energy resource for providing such supplementary generation applications. On-site ESS at PV integrated EV charging stations can use the TOU wholesale electricity pricing, which varies every half hour [104]. Hence, along with minimizing the wait time for commercial EV users these resources can also be made economically feasible in reducing the cost of commercial charging station operation. This chapter discusses the state-of-the-art in EV charging and use of renewable and ESS for the EV charging station available in the literature. The problems in the existing literature have been identified along with the possible solutions to mitigate them. It is then followed by the description of the proposed system configuration and detailed working of proposed hybrid optimization algorithm. In the end, the economic analysis for the subsidy to be provided by government agencies for higher POV penetration is provided for the

charging stations designed to serve private EVs and commercial EVs.

4.1 State-of-the-art

4.1.1 EV charging optimization algorithms

From the load point of view, for reducing the problems arising due to EV charging such as voltage deviation, frequency variation and THD, most of the recent research focuses on coordinating the EV charging. The authors in [7] aim for minimizing power losses and reducing voltage deviation while the authors in [67] describe maximizing the power delivery without adding burden to the existing grid. Various charge control methods are also proposed by the authors in [59,68].

To achieve sustainable integration of the transportation and electric network, the authors in [69] have proposed intelligent scheduling of EVs as loads and sources, whereas charging and discharging costs of the EVs are minimized in [70] for overnight demand shaping. EV charging scheduling is also implemented in [71] with particle swarm optimization under dynamic electricity pricing. The author in [68] proposes a two-stage mechanism for massive EV charging in which a fast charging rate compression algorithm being implemented for EV charging optimization. However, this may increase the charging time for the EVs.

Many researchers have carried out energy storage management for integration of EVs into the grid. To date, most of them mainly deal with energy storage management of batteries inside EVs. Figure 4.1 [10] represents the similar work where charging/discharging of lithium-ion battery inside EV is controlled in order to adjust to grid variability. Figure 4.1 shows the components of EV - Li-ion battery, battery charger and battery management system (BMS) unit fitted inside the EV. This is the typical EV structure that is followed by major EV manufacturers. The BMS unit is connected to external electric vehicle supply equipment during the charging and discharging process. The EV user usually have the control over the arrival time, departure time and desired SOC of EV upon departure. In order to control the charging/discharging rate of EV, the

aggregator controls the BMS of EV based on inputs from the EV user. In this way, the charging/discharging rate of the battery inside the EV is controlled for satisfying the grid constraints.

Figure 4.1: General model followed in literature survey [10]

From the literature survey it is found that this model is the most general one and is followed by most of the researchers till now. Authors in [72] proposed various charge scheduling algorithms for EV charging in the grid-to-vehicle (G2V) scenarios and vehicle-to-grid (V2G) scenarios. In all these scenarios where charging rate of EV is controlled, EV charging time is always compromised.

The drawback identified from the literature survey [68, 72] is that EVs have to wait or charge with low charging power due to charge scheduling algorithms. However, this is not a practical solution when large number of commercial EVs will penetrate. It is also not realizable in real world if we consider today's scenario, where gas stations fill the cars immediately and as required. Such gas stations will be replaced by the charging stations in future while customer expectations remaining the same. The focus in this study is given on the consideration that there should not be any delay in the charging event of EV once it is connected to the charging station. However, this problem can be tackled using energy storage systems for EV charging stations. This will serve as a buffer

between the grid and the EVs. Also, EVs should not be kept waiting for long hours to get charged. Another advantage of deploying ESS between the grid and EVs is to utilize variations in the electricity prices of the wholesale electricity market, optimizing the cost-effectiveness of the ESS for this application.

4.1.2 Renewable energy for EV charging applications

In most of the literature, EV charging load is mainly fed by the distribution grid, for which conventional generation units are the major sources. This surpasses the actual intention of adopting EVs as a green solution since power fed to these EVs is taken from non-renewable energy sources. This adds to carbon footprint. According to Paris Agreement on Climate Change, more than 180 countries have agreed to take initiative towards reducing the global warming and increasing the share of green energy sources [3].

To achieve this, Singapore has planned to raise the solar power generation to 350MWp by 2020, representing about 5% percent of peak electricity demand [73]. Falling prices of PV systems and continued market demand are expected to accelerate the adoption of solar energy. Hence, the use of PV as much as possible for charging EVs at charging stations would be the true green solution in reducing the carbon footprint. The PV integrated EV charging station especially RES-based one fits the requirement. This is not well explored [2], and needs to be analyzed further.

4.1.3 Energy storage for EV charging stations

With the rapid growth in dynamic loads such as EV charging, there are three major requirements from the distribution side:

1. Quick energy injection into the source or the grid.
2. Quick energy extraction from the source or the grid.
3. Dynamic response rather than long term serving capacity of source or grid.

ESS fulfills all of the above mentioned requirements for integrating EV charging station load into the existing system. While implementing energy storage within the grid has many benefits, the cost of the storage unit must be taken into account. The inclusion of an ESS will incur an additional cost associated with storage [74, 75]. The benefit of the ESS to any energy system requires an analysis on economic viability of ESS in that system.

A proper economic analysis needs the construction and the operating cost to be compared against the predicted profitability of the ESS in operating conditions experienced at the installation-site. Through a better understanding of the costs and financial benefit provided by a grid-connected ESS, power system operations optimize their systems for easier integration of ESS systems into their grid. Improper management of the ESS can incur large costs for the operator due to improper charging and discharging times. The hybrid optimization algorithm proposed in this study optimizes the operation of ESS for economic cost and benefit.

4.1.4 Major contributions of this study

The main contributions are as follows:

1. Cost degradation model for ESS is formulated which takes into account the number of life cycles of ESS (N_b) before reaching its end of life (EOL), and the capital cost of ESS (C_{ESS}). To the best of the author's knowledge, this type of ESS degradation cost formulation is not well explored in literature. Previous works on battery degradation [10, 11, 105–107] focuses on capacity fade and lifetime assessments of small scale lithium ion batteries fitted inside EVs. The battery degradation models in [108–110] deal with the analysis of battery degradation for supporting the distribution grid. These models mainly discuss the degradation of electrical characteristics and lifetime of ESS. However, the ESS degradation model proposed in this study is suitable for grid-scale applications of EV charging stations in the range of several hundreds of kWh. It mainly relates the operation of ESS to the cost of the operation. Hence, the ESS cost is fully justified based on

its use. The existing methods in literature would help in prolonging the lifetime as well as calculating the capacity fade more precisely. This would only enhance the proposed degradation model of this study and make it more accurate. Also, the proposed model is robust and is applicable for any kind of ESS technology and not only lithium ion batteries. Therefore, the study is reproducible with different types of ESS technologies to find their suitability for EV charging stations.

2. WEP is processed and analyzed before giving as an input to hybrid optimization algorithm. Upper band (UB) and lower band (LB) for WEP are calculated in real-time based on historical and projected electricity prices obtained from market operator in real-time. Instantaneous WEP is then compared with these bands. One of the advantage of this method is that the UB and the LB would dynamically adapt to the increase and decrease in WEP, as volatility increases and decreases. Therefore, the bands would naturally widen, and get narrow in synchronization with the price action, creating an accurate ranging envelope. This method provides the breakout points where the instantaneous WEP goes beyond the ranging envelop and influence the operation of proposed algorithm.
3. The hybrid optimization algorithm is formulated in such a way that it does not require forecasting of PV power and EV charging load. The algorithm performs optimization with real-time data, hence the optimization procedure is simplified. It is also capable of working with any kind of ESS and dynamic load, hence it is robust in nature. It achieves all these while satisfying 100% load at all time.
4. This study provides detailed analysis on subsidy evaluation for integrating PV system into EV charging application. It will be beneficial in planning of economic deployment of RES and ESS for EV charging applications to achieve higher penetration of RES in global efforts towards climate change.

4.2 System model

The proposed system in this part of study is shown in Figure 4.2. The proposed system shows an explicit use of ESS along with PV sources. The variation in power from the PV would be controlled by the ESS. The Energy Management System (EMS) block performs the acquisition of EV parameters based on the formulations proposed in [58], wholesale electricity prices from electricity market [104], PV power generation and ESS parameters such as state of charge and charge/discharge limits. Based on these inputs, the proposed algorithm decides whether to charge or discharge the ESS, the output from PV, power to be imported from the grid while serving 100% EV charging load at all time.

The system ensures that all the EV charging loads get served at the EV charging station at all circumstances. Thus, the proposed hybrid optimization algorithm is novel in this aspect, which is missing in literature.

Figure 4.2: Proposed system configuration

4.2.1 EV charging stations

The EV charging model is derived from chapter 3 with variation in parameters. However, the algorithm proposed in this part of the study considers this load model merely as an

input to the system, and it would work for any types of EV charging load model. The statistical (corresponding to model with all private EV users) and uncoordinated EV charging load (corresponding to model with all commercial EV users) are shown in Figure 4.3.

Figure 4.3: Statistical and Uncoordinated EV charging loads considered for this study

The statistical EV charging model can be constructed for any area, where EV charging station is located and arrival/departure statistics can be obtained. The uncoordinated EV charging behavior is governed mainly by the commercial EVs, i.e., electric taxis, with a high level of uncertainty in arrival/departure times. It is reflected in the load demand spread across the 24 hour due to all day operation of these EVs. It can also be observed from Figure 4.3 that the peak power required by uncoordinated charging behavior of EVs is more than the statistical EV charging. This load is calculated in real-time for every minute in NetLogo, and given as an input to the proposed algorithm. These two extremes of the EV categories are chosen to verify the feasibility of the algorithm for EV charging load of two completely different nature.

4.2.2 Energy storage systems

Lithium-ion batteries are considered as ESS in our study. Battery degradation is typically caused by three major factors, temperature, depth of discharge (DOD) and SOC [10]. These three factors would reduce the charging/discharging cycles of the ESS, affecting their performance. This in turn degrades the cost associated with its purchase. The cost of use of ESS for grid operation is hereafter termed as battery degradation cost.

The parameters considered during the calculation of ESS degradation cost are explained as follows:

1. Charging rate of battery: It is defined as the portion of energy that is supplied to a battery in one hour and is usually denoted as C or C-rate. For example, if a battery with nominal capacity of 16Ah is charged using 2A current, then the charging rate is 1/8 C and it will approximately take 8-10 hours for charging the battery depending on its characteristics.
2. Battery charging power: This is the total power fed into the battery every minute of its operation. This parameter is used while calculating degradation cost due to charging operation.
3. Battery discharging power: This is the total power supplied by the battery every minute of its operation. This parameter is used while calculating degradation cost due to discharging operation.
4. Capital cost of battery: This is the cost of procurement and setup of battery modules and converters.
5. Battery capacity: This is the total capacity of battery energy storage system.
6. Maximum charging and discharging power: The life of lithium-ion batteries is greatly affected by their charge/discharge rates. Hence it is necessary to always maintain charging and discharging power from the battery lower than its maximum withstand capacity to avoid stress on battery.
7. Life cycles of battery before reaching end of life: This parameters states the number

of cycles of operations the battery will perform till its capacity fades up to 70% of its initial capacity.

8. Charging and discharging efficiency: These efficiencies comprises the battery cycle efficiency as well as converter efficiency while charging and discharging operation.

Every ESS has a fixed number of cycles to operate until it reaches the EOL. These number of cycles are usually specified by the ESS manufacturers. At each charge and discharge operation of ESS, ESS loses one cycle of life. Hence the ESS degradation cost calculated based on the capital investment cost of ESS procurement and total number of charge/discharge cycles is more realistic. The battery degradation cost is calculated in terms of the number of cycles (N_b) of charging/discharging, which in turn is based on cumulative effect of temperature, DOD and SOC. Therefore, the current form of the degradation cost formulation does not require explicit consideration of these aging factors. This study focuses more on the economic operation of ESS. Since the entire cost of ESS is spread over N_b , the degradation cost is accounted till the EOL of ESS, representing the LCOE of ESS over its N_b cycles. Battery manufacturers often mention the number of cycles that the batteries can operate before reaching their EOL. When ESS completes one charging and one discharging operation, it is counted towards one complete cycle of operation. During the operation of ESS, the average number of hours ESS charges or discharges in a day is measured. This information is processed to generate the number of cycles of operation completed by the ESS at the end of each iteration. The cost associated with the one complete cycle is then used for the further economic analysis of the ESS operation in the charging station.

The minute-wise battery degradation cost is split into two parts, i.e., degradation due to charging and degradation due to discharging. Battery degradation with respect to the number of cycles is calculated as

$$C_{bd}(t) = C_{bd\,cha}(t) + C_{bd\,dis}(t), \quad (4.1)$$

$$C_{bdch}(t) = \frac{\zeta P_{bc}(t) \eta_{bc} C_{ESS}}{T_{bc} B_{ESS} N_b \tau}, \quad (4.2)$$

where $P_{bc} \in \mathbb{R}; t \in \{0, 1, 2, \dots, T\}$.

$$C_{bd dis}(t) = \frac{(1 - \zeta) P_{bd'}(t) C_{ESS}}{T_{bd} B_{ESS} N_b \eta_{bd} \tau}, \quad (4.3)$$

where $P_{bd'} \in \mathbb{R}; t \in \{0, 1, 2, \dots, T\}$.

In eqn. 4.2, at first, C_{ESS} is split into N_b parts. The $P_{bc}(t)$ as a fraction of the total energy capacity of ESS (B_{ESS}) is divided by the average number of hours ESS charges in a day (T_{bc}). This gives the degradation due to each kW power injected in ESS per hour. The entire equation is then multiplied by the ratio of ζ and τ , giving the degradation cost of ESS each minute, with $\tau = 60$. Eqn. 4.3 follows the similar method during discharging mode of operation.

4.2.3 Economic analysis of electricity market in Singapore

In the Singapore's energy market, eligible consumers can opt for buying electricity at the wholesale electricity price (WEP) from the wholesale electricity market [104]. WEP is highly volatile, getting updated every half-hourly. Therefore, it can be considered as a ranging market. Ranging market is the term used for the markets which keep oscillating between high price values and low price values during entire day.

The analysis of WEP for using ESS at EV charging stations is important in

1. Providing an additional option for consumers to manage their electricity usage in response to price signals.
2. Reducing the wholesale electricity prices during peak periods as more expensive generation units need not be scheduled to run.
3. Promoting more efficient investments in power generation by reducing need to invest in expensive generation units that are only run intermittently to meet peak demand.

4. Providing an additional resource to improve system reliability as consumers reduce consumption in response to high prices during periods when supply capacity is low e.g., due to unplanned outages or gas disruptions.

Hence, a careful analysis of the wholesale electricity market is necessary to exploit maximum benefit out of its price variation.

4.3 Price band allocation method

The authors in [11] uses the current electricity price as it is, in optimization algorithms without any processing on electricity prices. If the electricity prices are processed before giving as input to an optimization problem, a considerable amount of processing time as well as the complexity of the algorithm can be reduced. The band allocation method shifts the optimization problem from deterministic to heuristic and vice versa, for the range of time intervals based on price bands. This is achieved as follows:

1. Calculate the moving average of electricity prices.
2. Calculate the upper and lower band of electricity prices.
3. Compare electricity price at any instant with its band limits before giving input to the optimization problem.

Moving averages smoothen the price data to form a trend following the indicator. They do not predict the price direction, but rather define the current direction with a lag. Moving averages lag because they are based on past prices. Despite this lag, moving averages help smooth price action and filter out the noise. They also form the building blocks for many other technical indicators and overlays, such as Bollinger Bands. One of the most popular types of moving averages is the Simple Moving Average (SMA). This moving average method can be used to identify the direction of the WEP trend.

A simple moving average is formed by computing the average price of a electricity over a specific number of periods. A 20-day simple moving average is the twenty day sum of prices divided by twenty. As its name implies, a moving average is an average

that moves. Old data is dropped as new data becomes available. This causes the average to move along the time scale.

$$SMA(t) = \frac{\sum_{k=-n}^n R(k)}{2n}. \quad (4.4)$$

The direction of the moving average conveys important information about prices. A rising moving average shows that prices are generally increasing. A falling moving average indicates that prices, on average, are falling. A rising long-term moving average reflects a long-term uptrend. A falling long-term moving average reflects a long-term downtrend.

Historical data up to 48 time periods and data forecast for next 48 hours are obtained from the energy market company [104]. The upper and lower price limits based analysis of these values are calculated to implement the TOU pricing. This is achieved by calculating SMA at every half-hourly (one time period for price band calculation). Twenty past and twenty forecast values (n) taken from the market operator in real-time are used for calculating SMA. UB and LB are calculated by adding and subtracting 0.5 standard deviation (σ_R) from this SMA as shown in eqns. 4.5 and 4.6 respectively. The WEP, SMA and the price bands are shown in Figure 4.4. These price bands will be calculated once in every half-hour at the beginning of each time period, and will remain the same throughout the time period until WEP changes after one half hour.

Figure 4.4: Wholesale Electricity price for a typical day and price band allocation

$$UB = SMA(k) + 0.5 \sigma_R(k) \quad (4.5)$$

$$LB = SMA(k) - 0.5 \sigma_R(k) \quad (4.6)$$

where,

$$\sigma_R(k) = \sqrt{\frac{1}{2n-1} \sum_{k=k-n}^{k+n} (R(k) - SMA(k))^2} \quad (4.7)$$

Synchronized with the price action, these bands would naturally widen and get narrowed, creating an accurate ranging envelope.

4.3.1 Configuration and LCOE of PV system

The PV system in this study is of 75 kW rated capacity. The PV power is calculated every minute, based on the solar irradiance data $I_S(t)$, measured at the rooftop in Singapore and available at [99]. The charging station considered in our study can accommodate 264 PV panels on its rooftop. This is calculated based on minimum area required for 20 EV parking according to the LTA parking guidelines in Singapore [97]. The total power generated by the PV system is calculated as

$$P_{PV}(t) = I_S(t) A_{PV} N_{PV} \eta_{PV} \quad (4.8)$$

The LCOE is widely used to evaluate the cost of electricity generation of different technologies over the plant lifetime. It includes initial construction costs, costs of operation and maintenance, cost of fuel, and the cost of capital. The LCOE of PV system is based on the study provided by the authors from Solar Energy Research Institute of Singapore in [112]. LCOE of the PV system calculated in [112] is used for the cost optimization problem in Section IV, however the process of calculation of LCOE as mentioned in [112] is beyond the scope of this thesis. Hence it is not covered in this thesis.

4.4 Problem formulation and algorithm

The optimization problem can be formulated as,

$$\arg \min J, J = C_g(t) + C_{bd}(t) + C_{PV}(t) \quad (4.9)$$

where, $C_{bd}(t)$ is taken from equation 4.1.

$$C_g(t) = R(t) P_g(t), P_g \in \mathbb{R} \quad (4.10)$$

$$C_{PV}(t) = LCOE_{PV} P_{PV}(t) \quad (4.11)$$

where, $P_{PV}(t)$ is taken from equation 4.8.

Thus, equation 4.9 can be rewritten as

$$\arg \min J, J = R(t)P_g(t) + \frac{\zeta P_{bc}(t) \eta_{bc} C_{bat}}{T_{bc} B_{ESS} N \tau} + \frac{(1 - \zeta) P_{bd}(t) C_{bat}}{T_{bd} B_{ESS} N \eta_{bd} \tau} + C_{PV}(t) \quad (4.12)$$

subject to

$$P_L(t) = P_g(t) + P_{bd}(t) - P_{bc}(t) + P_{PV} \quad (4.13)$$

$$P_{bc}(t) P_{bd}(t) = 0 \quad (4.14)$$

$$0 < P_{bc}(t) < P_{bcMax} \quad (4.15)$$

$$0 < P_{bd}(t) < P_{bdMax} \quad (4.16)$$

$$0.25 < E_b(t) < 0.90 \quad (4.17)$$

The energy capacity of ESS is updated every minute as

$$E_b(t) = E_b(t - 1) + \frac{P_{bc}(t) B_{ESS}}{P_{ICb} \tau} - \frac{P_{bd}(t) B_{ESS}}{P_{ICb} \tau} \quad (4.18)$$

The above mentioned optimization problem turns out to be a linear programming problem. The proposed algorithm as shown in Figure 4.5 changes the approach from the

rule-based approach to deterministic approach, and vice versa in real-time depending on the value of $R(t)$. If $R(t)$ is within the UB and the LB calculated from eqns. 4.5 and 4.6, the algorithm solves the linear programming problem using the MATLAB fmincon solver. If $R(t)$ is greater than the UB or less than the LB, the algorithm solves the problem with predefined rules.

Here, the focus is to model the system for a realistic problem which does not require the use of high efficient solver to minimize the time. The computation speed of the MATLAB built-in fmincon solver was well within the acceptable range of the need of problem solution.

$R(t)$, E_b , P_{PV} and P_L are provided as the inputs, whereas P_g , P_{bc} , P_{bd} are taken as the outputs from the hybrid optimization algorithm at every instant t . Here, t is considered as 1 minute, $0 < t \leq 1440$ for one day operation.

Algorithm 1 shows the rule-based approach when $R(t)$ is greater than UB. In this case, the algorithm first checks the constraints of E_b and values of P_{PV} and P_L at t . If $25\% \leq E_b \leq 90\%$ and $P_{PV} \geq P_L$, which means that PV generation is higher than EV charging load and ESS has a capacity to store the surplus amount of energy, Algorithm 1 calculates the power to be stored in ESS while fulfilling the entire EV charging load. If $E_b \geq 90\%$ with all other previous conditions the same, the surplus energy would be sold to grid.

Further in Algorithm 1, if $P_L > P_{PV}$, and $E_b \geq 25\%$, the additional power to be supplied to load is extracted from ESS. If $P_L > (P_{PV} + P_{bd})$ then the additional power is imported from the grid. The P_{bc} to be injected and P_{bd} to be extracted from ESS are decided based on the constraints i.e. maximum charging power P_{bcMax} and maximum discharging power P_{bdMax} of ESS respectively. These values are to be chosen based on ESS specifications. In the situation where $E_b < 25\%$, whenever $P_{PV} > P_L$ the surplus energy from PV will be stored in ESS and whenever $P_{PV} < P_L$ the additional power required for EV charging load will be supplied by the grid.

Algorithm 1 prioritizes extracting power from ESS over importing power from the grid whenever PV generation is not enough to meet EV charging load.

Figure 4.5: Flowchart for hybrid optimization algorithm

Algorithm 1 Algorithm for $R(t) > \text{Upper Band}$

Input: $R(t), E_b, P_{PV}, P_L$ **Output:** P_g, P_{bc}, P_{bd} *Initialization* : As mentioned in Table 4.1

```
1: for  $t = 1$  to 1440 do
2:   if  $E_b \geq 0.25$  then
3:     if  $P_{PV} \geq P_L$  then
4:       if  $E_b < 0.90$  then
5:         if  $P_{PV} - P_L \geq P_{bcMax}$  then
6:            $P_{bc} = P_{bcMax}, P_{bd} = 0, P_g = -(P_{PV} - P_L + P_{bc})$ 
7:         end if
8:          $P_{bc} = P_{PV} - P_L, P_{bd} = 0, P_g = 0$ 
9:       end if
10:       $P_{bc} = 0, P_{bd} = 0, P_g = -(P_{PV} - P_L$ 
11:    end if
12:    if  $P_L - P_{PV} > P_{bdMax}$  then
13:       $P_{bd} = P_{bdMax}, P_{bc} = 0, P_g = P_L - P_{bd} - P_{PV}$ 
14:    end if
15:     $P_{bd} = P_L - P_{PV}, P_{bc} = 0, P_g = 0$ 
16:  end if
17:  if  $P_{PV} \geq P_L$  then
18:    if  $P_{PV} - P_L \geq P_{bcMax}$  then
19:       $P_{bc} = P_{bcMax}, P_{bd} = 0, P_g = -(P_L - P_{PV} + P_{bc})$ 
20:    end if
21:     $P_{bc} = P - PV - P_L$ 
22:  end if
23:   $P_{bc} = 0, P_{bd} = 0, P_g = PL - P_{PV}$ 
24: end for
25: return  $P_g, P_{bc}, P_{bd}$ 
```

Algorithm 2 shows the rule-based approach when $R(t)$ is lower than LB. In this case, the algorithm first checks the constraints of E_b and values of P_{PV} and P_L at t . If $E_b < 90\%$ and $P_{PV} \geq P_L$, which means that PV generation is higher than EV charging load and ESS has a capacity to store the surplus amount of energy, Algorithm 2 stores the surplus amount of energy into ESS. If this surplus energy is less than P_{bcMax} then additional power is imported from the grid to charge ESS at P_{bcMax} . If $E_b \geq 90\%$ with all other previous conditions the same, the surplus energy would be sold to grid.

Further in Algorithm 2, if $P_L > P_{PV}$, and $E_b < 90\%$, additional power to be supplied to load together with P_{bcMax} is imported from grid. The P_{bc} is constrained with maximum charging power P_{bcMax} based on ESS specifications.

Algorithm 2 prioritizes importing power from the grid for charging ESS at P_{bcMax} together with the EV charging load demand.

Algorithm 2 Algorithm for $R(t) < \text{Lower Band}$

Input: $R(t), E_b, P_{PV}, P_L$

Output: P_g, P_{bc}, P_{bd}

Initialization : As mentioned in Table 4.1

```

for  $t = 1$  to 1440 do
2:   if  $E_b < 0.90$  then
       if  $P_{PV} \geq P_L$  then
4:       if  $P_{PV} - P_L \geq P_{bcMax}$  then
            $P_{bc} = P_{bcMax}, P_{bd} = 0, P_g = -(P_{PV} - P_L - P_{bc})$ 
6:       end if
            $P_{bc} = P_{bcMax}, P_g = P_{bcMax} - P_{PV} + P_L, P_{bd} = 0$ 
8:       end if
            $P_{bc} = P_{bcMax}, P_{bd} = 0, P_g = P_{bcMax} + P_L - P_{PV}$ 
10:    end if
       if  $P_{PV} \geq P_L$  then
12:        $P_g = -(P_{PV} - P_L), P_{bd} = 0, P_{bc} = 0$ 
       end if
14:     $P_g = P_L - P_{PV}, P_{bd} = 0, P_{bc} = 0$ 
       end for
16: return  $P_g, P_{bc}, P_{bd}$ 

```

4.5 Case Study

To check the effectiveness of the proposed hybrid algorithm, the following three test cases are considered.

1. The EV charging station without ESS and PV

This case scenario is generated to get the running cost of the EV charging station when ESS and PV are unavailable. The total charging power of the EVs is fed from the grid.

2. The EV charging station with ESS and without PV

This test case is generated to evaluate the proposed algorithm for deploying ESS near to the EV charging station, when no RES is available nearby. Simulation for this test case is performed in two ways. Firstly, the entire optimization function is

solved using the deterministic approach, without applying the price band allocation method. The WEP is directly taken as input at first and the cost of electricity purchased from the grid is calculated for statistical as well as uncoordinated EV charging load. Secondly, the objective function is solved using our proposed hybrid optimization algorithm. When the real-time WEP is taken as an input, the proposed algorithm takes the decision to solve the problem either by the rule-based or deterministic approach. The results from both sides are then compared and discussed.

3. The EV charging station with ESS and PV

This test case is generated to evaluate the effectiveness of deploying ESS with our proposed algorithm in the PV integrated EV charging station. Similar to the previous test case, this test case is also evaluated in two ways. It differs from the previous test case due to the LCOE of PV, which is considered in this case. The realistic solar irradiation data of Singapore [99] is used as input for the calculation of PV power.

4.6 Results

In order to test the algorithm, the real-time charging scenario through uncoordinated and statistical charging formulations using ABM of EV charging is created to resemble the real-time EV charging behavior. The OCS load profile used in this case has the peak demand of 272.59 kW. The input parameters for the system are mentioned in Table 4.1. The ESS parameters are taken from the specifications of the SAFT Intensium Max battery [113]. It is assumed that the temperature around ESS is always maintained constant at 25°C which is valid in the context of Singapore. Hence, the degradation due to rise in temperature is neglected. The real WEP for January 2016 obtained from EMC Singapore is considered for these test cases [104]. Linear programming optimization is solved using two solvers, ‘fmincon’ solver in MATLAB and CPLEX. The LPMethod parameter in CPLEX is set ‘0’ while solving the model. This let the CPLEX choose the solver

automatically which fits best to the linear programming problem. An analysis of the results is performed after running the simulation for all 7 days of a week with each day's WEP. This procedure is repeated for several weeks period time to observe and examine the results from algorithm.

Table 4.1: System parameters

Parameter	Value	Parameter	Value
Initial E_b of ESS%	75%	$LCOE_{PV}$	0.24 SGD/kW [112]
Ambient Temp	25 °C	P_{bcMax}	150 kWp [113]
N_b	6000	P_{bdMax}	150 kWp [113]
C_{ESS}	SGD 400/kWh	η_c	0.95 [113]
B_{ESS}	620kWh	η_d	0.95 [113]
T_{bc}	5 hours	η_{pv}	16.4%
T_{bd}	5 hours	A_{PV}	1.75 sq.m

The optimization results for the second test case are shown in Figure 4.6. It can be observed from Plot(IV), at $T = 9$ to $T = 11$ and $T = 13$ to $T = 15$, of Figure 4.6, that the proposed algorithm has successfully shifted all load requirement to ESS for $R(t) > UB$. Also, in Plot(III)-(V), between $T = 9$ to $T = 11$ and $T = 21$ to $T = 23$, the optimizer invokes power exchange between the grid and the ESS for $UB > R(t) > LB$, until E_b goes below 25%. It can also be seen from Plot(V) of Figure 4.6, that at $T = 12$ to $T = 13$, and $T = 17$ to $T = 20$, the ESS was charged, when $R(t) < LB$, until E_b reaches 90%. The cost of electricity purchased from the grid with ESS is found to be lower than the system without ESS. At all the time instances, the proposed algorithm has successfully fulfilled 100% EV charging load, shown in Plot(II) of Figure 4.6. This can be verified by the summation of results at all time instances in Plot(II)-Plot(V) of Figure 4.6, as mentioned in equation .

Table 4.2 and Table 4.3 show the results for cost of the energy purchased from the grid in SGD for EV charging station for the test cases: without ESS, with ESS and only deterministic approach and with ESS and proposed hybrid algorithm; using fmincon solver for private and commercial EV charging loads respectively for one of the weeks in January 2016, '10th January to 16th January'. Table 4.4 and Table 4.5 shows the results for the same test cases and scenarios obtained using the CPLEX. These tables

Figure 4.6: Hourly power plot for one day, Plot (I) Electricity Price, Plot (II) Load requirement, Plot (III) Grid power, Plot (IV) Battery discharge power, Plot (V) Battery charging power for commercial Load and SMA

clearly indicate that it is feasible to deploy the ESS at EV charging station for both entirely the private as well as entirely commercial type of the EV charging load.

Table 4.2: Total cost of system in SGD/day using all private EV charging load model and solved using fmincon

Day	Cost with ESS Optimisation	Cost With ESS deterministic approach	Cost Without ESS
10th Jan	83.30	89.94	86.30
11th Jan	97.80	102.37	104.56
12th Jan	88.23	88.54	95.03
13th Jan	116.01	118.46	142.43
14th Jan	88.56	90.79	98.72
15th Jan	74.89	76.65	75.75
16th Jan	64.60	65.13	74.68
Weekly Cost	613.39	631.88	677.47

Table 4.3: Total cost of system in SGD/day for all commercial EV charging load model and solved using fmincon

Day	Cost with ESS Optimisation	Cost With ESS deterministic approach	Cost Without ESS
10th Jan	266.98	301.86	298.76
11th Jan	326.76	369.56	357.12
12th Jan	302.14	336.15	323.28
13th Jan	411.69	503.23	490.11
14th Jan	303.18	338.40	344.18
15th Jan	254.95	274.88	264.31
16th Jan	218.06	238.02	226.20
Weekly Cost	2083.76	2362.10	2303.96

Table 4.4: Total cost of system in SGD/day for all private EV charging load model and solved using CPLEX

Day	Cost with ESS	Cost with ESS deterministic approach	Cost Without ESS
10th Jan	82.14	88.56	86.30
11th Jan	95.25	99.82	104.56
12th Jan	86.98	87.52	95.03
13th Jan	113.86	117.79	142.43
14th Jan	86.04	88.54	98.72
15th Jan	73.73	74.15	75.75
16th Jan	63.37	62.81	74.68
Weekly Cost	601.36	619.19	677.47

Table 4.5: Total cost of system in SGD/day for all commercial EV charging load model and solved using CPLEX

Day	Cost with ESS	Cost with ESS deterministic approach	Cost Without ESS
10th Jan	266.69	301.23	298.76
11th Jan	325.93	367.86	357.12
12th Jan	301.02	334.02	323.28
13th Jan	410.80	502.56	490.11
14th Jan	301.53	337.76	344.18
15th Jan	252.86	272.92	264.31
16th Jan	217.47	236.59	226.20
Weekly Cost	2076.31	2352.94	2303.96

The results from fmincon and CPLEX are compared in the Table 4.6 and Table 4.7. It is observed that CPLEX has solved the problem more accurately in all the scenarios of all private and all commercial EV charging. The weekly cost of operation for the all private EV charging scenario using CPLEX is found to be \$12.03 and \$12.69 lesser compared to the results obtained from fmincon solver for the case of with and without price bands respectively. While for all commercial EV charging scenario, it is \$7.45 and \$9.46 for the case of with and without price bands respectively. The difference between the savings obtained in these two cases by using fmincon and CPLEX is found to be \$0.66 for all private EV charging scenario and \$1.71 for all commercial EV charging scenario.

Table 4.6: Comparison of results in SGD: All private EV charging load

Solver	Cost with ESS and price bands	Cost with ESS and without price bands	Weekly saving
fmincon	613.39	631.88	18.49
CPLEX	601.36	619.19	17.83
Difference	12.03	12.69	0.66

Table 4.7: Comparison of results in SGD: All commercial EV charging load

Solver	Cost with ESS and price bands	Cost with ESS and without price bands	Weekly saving
fmincon	2083.76	2362.10	278.34
CPLEX	2076.31	2352.94	276.63
Difference	7.45	9.16	1.71

Results show that in some cases though the saving is very less as compared to electricity cost without ESS, the algorithm has successfully managed not to exceed the running cost of the system with ESS. Comparing the cost savings between Table 4.6 and Table 4.7, savings with commercial charging are more than those of the private EV charging load model, which suggests that with an increased and evenly distributed load throughout the day, it is more economical to deploy the ESS. However, the savings obtained show some variation. This variation is due to highly volatile nature of WEP. The ESS has successfully reduced its dependency on the grid during high WEP hours. Also, the ESS has clipped the peaks in load demand from passing over to the grid during intermittent peak pricing hours, i.e., when $UB > R(t) > LB$.

The results in Table 4.6 and Table 4.7 also show the reduction in cost of EV charging operation using the addition of price band segregation method applied in the proposed algorithm when compared to the complete deterministic approach without price band segregation. Each iteration of the proposed algorithm is solved at the beginning of each minute. The results are obtained in less than ‘1’ second for all cases. In case of the complete deterministic approach, various other solvers and optimization techniques can solve the problem faster owing to reduced complexity. However, the reduction in computational time is insignificant in the scenarios of the EV charging application considered here. Hence, the proposed algorithm has an advantage of simpler formulation, robustness and proven cost reduction in the PV integrated EV charging operation.

4.6.1 PV subsidy analysis

Figures 4.7, 4.8, 4.9 and 4.10 shows the four weeks results obtained from the simulation, for the cost of electricity purchased from the grid for the PV integrated EV charging station with ESS using entirely the private EV charging load model. Various levels of subsidy (in %) provided in the PV system is also shown. The complete ESS degradation cost is considered during the optimization of this test case. Figures 4.11, 4.12, 4.13 and 4.14 shows the same details for commercial EV charging load for a period of four weeks. During the simulation, the percentage of subsidy on PV system is increased gradually

in the steps of 5% to check the optimum point, where the cost ‘without ESS and PV’ matches with the cost of ‘ESS and subsidized PV’. This procedure is repeated for four consecutive weeks of January 2016, with its real-time WEP for each day. The results of subsidy analysis are shown in Figures 4.8, 4.9 and 4.10 for private EVs and for Figures 4.12, 4.13 and 4.14 commercial EVs.

The results obtained for each week as shown in above Figures proves that with the given configuration of the EV charging station, up to 40% subsidy in the PV system is required for the private EV charging load, and up to 5% subsidy is required for the commercial EV charging load. This drastic reduction in requirement of subsidy indicates that with a higher and evenly distributed EV charging load across the day, the ESS and the PV system would be more economical with the proposed algorithm. The commercial EV charging provides an added scope for the proposed algorithm to exploit the benefit of ESS and half hourly changing WEP compared to the private EV charging load. The proposed algorithm is robust to adapt to different configurations of the EV charging station, ESS and PV system.

Figure 4.7: Weekly running cost of private EVs for various % of PV subsidy

Figure 4.8: Weekly running cost of private EVs for various % of PV subsidy

Figure 4.9: Weekly running cost of private EVs for various % of PV subsidy

Figure 4.10: Weekly running cost of private EVs for various % of PV subsidy

Figure 4.11: Weekly running cost of commercial EVs for various % of PV subsidy

Figure 4.12: Weekly running cost of commercial EVs for various % of PV subsidy

Figure 4.13: Weekly running cost of commercial EVs for various % of PV subsidy

Figure 4.14: Weekly running cost of commercial EVs for various % of PV subsidy

4.7 Discussion

The study presented in this chapter optimizes the charging/discharging power from the ESS, and the power to be imported from grid based on price band allocation of the real-time WEP. The study presented in this chapter is an application demonstrating the extension of results obtained from chapter 3. Various case studies can be created by varying the parameters in ABM for EV charging as well as parameters in system model presented in this chapter.

1. The scope of this study is limited to energy storage management and calculation of the degradation cost of ESS, while fulfilling 100% EV charging load at all time. The proposed hybrid algorithm is robust to adapt any kind of EV load modeling process.

2. The proposed algorithm works best when the volatility in the wholesale electricity market is high, taking the advantages of the continuous change in WEP and adjusting its mode of operations between different approaches. The case where WEP remains flat for the entire day, UB and LB for all t would follow a constant trend. The $R(t)$ would always lie between UB and LB. Hence, parts of the proposed algorithm, Algorithm 1 and Algorithm 2, will not execute in this scenario. The optimization would be entirely solved using linear programming, i.e., deterministic approach. While the proposed algorithm ensures an optimum solution with flat electricity price, the ESS may not charge/discharge due to a high cost of operation. However, this is a limitation imposed by the market through a flat WEP trend, rather than a disadvantage for the algorithm itself. If the WEP is consistently having a flat trend, the need for TOU and WEP itself would be questionable, and it is not in the scope of the thesis. As the proposed algorithm is designed for maximizing the benefit of variations in WEP, a flat trend in WEP would not require complex procedures described in the proposed algorithm. It can be solved using a simple linear programming solver. To summarize, the proposed algorithm will be underutilized where the WEP trend is flat.
3. The cost of deploying ESS and PV is still rather high in today's power generation scenario, and expected to be lower in future with ongoing technical advances in both fields. Though prices are higher, global efforts like Paris agreement on climate change [3] and climate action plan [73] are motivating all countries to take preventive measures against carbon emissions. A higher penetration of EVs is a solution to reduce carbon emissions. In order to achieve these goals set by this agreement, adoption of ESS and RES is essential irrespective of its higher costs to counteract the problems created by EV charging.
4. This study brings in the subsidy analysis to help in better absorption of ESS and PV into the existing power system for EV charging applications until the cost of RES is lowered.
5. The scenario where EV load increases suddenly, the presented study shows that

a sudden increase in load would result in decrease in subsidy required for PV integration, as shown in Figure 4.7 and 4.11. This is because of higher utilization of variation in electricity price. However, all the components of this study are scaled for a single charging station. The present form of algorithm is evaluated to fit well when multiple charging stations of similar or lesser capacity are deployed at various places. In case of multiple charging stations, the proposed algorithm would be helpful in energy storage management between the individual charging station and grid. The combined operation of multiple charging station would then become a new microgrid optimization problem which needs additional layer of optimization for energy exchange among PV and ESS of all charging stations.

6. PV integrated EV charging stations deployed with ESS would reduce the power demand from grid during high price-peak hour whereas it would provide an opportunity for the grid to inject power into ESS and load during low price hours. This characteristic can be observed in Plot(III) of Figure 4.6. The average power imported from the grid is reduced when PV and ESS is deployed at the charging station compared to a scenario without PV and ESS. The entire EV charging load would have been supplied by the grid in the later case. Reducing the loads from the grid during peak hours in turn reduces the stress on conventional power generation sources. Reduction in each unit of energy is equivalent to generation of the same unit of energy at power plants. It would also reduce the burden on the distribution network where the charging stations would be located, as well as the corresponding transmission network. The effect of intermittency in PV generation is minimized due to presence of ESS as a buffer between PV and grid. Electricity markets worldwide are moving towards liberalization for more consumer participation. A PV integrated EV charging station with ESS allows active market participation for charging stations, which would also facilitate the dynamic pricing from market operators.
7. The results shown in Table 4.6 and Table 4.7 show that the proposed hybrid optimization algorithm provides the satisfactory results with the use of fmincon and

CPLEX solver. The novelty is proposed in terms of implementing price bands and use of ESS degradation cost with respect to its life cycles within the problem formulation and optimization process to minimize the cost of energy purchased from grid. The formulated problem is solved with and without implementing electricity price bands as an input to the problem. Both cases are evaluated by using same solver each time i.e. fmincon and CPLEX. The commercial solver like CPLEX has definitely produced more accurate results as evident from Table 4.6 and Table 4.7. However, the proposed method has always resulted in lower cost of the operation compared to the case without addition of electricity price bands. Hence, the use of any solver to compare both cases would yield to the similar conclusions.

4.8 Conclusions

The objective of this extensive economic analysis of PV-Integrated charging stations with on-site ESS is to minimize the EV charging cost with the help of ESS at PV integrated EV charging stations using TOU wholesale electricity pricing which varies every half hourly. A hybrid optimization algorithm which is combination of rule-based as well as deterministic approach is proposed in this study to meet the aforesaid objective. The wholesale electricity is first categorized into upper and lower price bands every half hour. The real-time electricity price is then checked against the real-time calculated bands. Subsequently decisions are taken by the algorithm to shift between the rule-based and deterministic modes. Hence, the algorithm is termed as the hybrid optimization algorithm.

During the deterministic mode of operation, the optimization problem is formulated. Using the real-time wholesale electricity price and EV load demand generated via the ABM of Chapter 3 as inputs, the algorithm provides decisions for energy storage management while fulfilling all EV charging load without violating the ESS constraints. The OCS load profile used has the peak demand of 272.59 kW. The proposed hybrid optimization algorithm is evaluated for two scenarios: with ESS deployed near EV charging

stations without rooftop PV, and another with ESS deployed near PV integrated EV charging stations. The first scenario is used for studying the feasibility of the ESS in the EV charging station. It is applicable to areas where EV integration is substantial but deployment of the PV system is not feasible due to less sunshine hours, such as Norway [114].

The degradation cost of ESS as well as the levelized cost of energy (LCOE) for PV are considered in this study to assess the economic feasibility of deploying ESS in the TOU-based energy storage management of PV integrated EV charging stations. Results obtained for this scenario show a significant amount of cost saving due to deployment of ESS in utilizing the TOU pricing of the wholesale electricity price (WEP). The cost of charging station operation for commercial and private EVs reduced by 8.6% by using the proposed algorithm with on-site EVs. Furthermore, the subsidy on the PV system to be provided by the government agencies is demonstrated with extensive simulation results considering solar irradiation and LCOE of PV. Due to the higher cost of the PV system, it has been observed that up to 40% subsidy is required on the PV system cost for the operation of charging station catering privately owned EVs. This subsidy decreases drastically to 5% when the same charging station caters to commercial EVs. The reduction in subsidy requirement is due to the higher utilization of ESS in using TOU pricing. Hence, it has been concluded that the amount of subsidy requirement on PV system reduces with a higher utilisation of ESS based on TOU prices. Results from the latter scenario are useful in analyzing realistic economical PV integration for EV charging applications, as the PV and ESS costs are still rather high compared to the costs of fossil fuel-based power generation.

Chapter 5

Conclusion and Recommendations for Future Research

This chapter provides an overall assessment of this thesis. The recommendations for the future research directions with regards to the extension of research in ABM for EV charging and the extension of energy storage management strategies for the operation of multiple EV charging stations are discussed.

5.1 Conclusion

In this thesis, a simulation model to predict the charging demand of EVs based on various essential parameters is proposed. The background of the ABM and techniques for its implementation is described in chapter 2. The forecasting methods used in literature previously have the limitations in generating repetitive charging demands and lacks the ability to adapt itself should any unexpected situation occurs in the charging process. The ability of ABM in responding itself according to the change in situation helps in predicting the behavior of EV users under various scenarios. Hence, this approach closely mimics the real world EV charging experience which traditional stochastic modelling techniques fails to achieve.

The results emphasize the practical applicability of the ABM based approach to predict the charging demand of EVs. The ABM approach accounted for various aspects of

EV charging including technical, social and economic parameters to ensure reliable results. The simulations were carried out for a 24-hour period over several days. Individual and total power demands at the charging stations are determined for various scenarios to enable a further analysis in real world situations. Furthermore, the proposed model also facilitated the analysis of both commercial EVs and private EVs by accounting for their respective usage patterns. The sensitivity analysis is presented at the end of chapter 3. The sensitivity analysis based on the proportion of commercial category vehicles signifies that EV charging stations capable of fully accommodating present charging requirements can accommodate 20% more EV penetration without significantly impacting peak demand of EV charging stations. This sensitivity analysis of user experience suggests that as EV users become more experienced, the frequent charging events are lowered resulting in lower charging demand. The power demand can be reduced up to 30% if the drivers are well aware about driving range of the EV battery. This highlights the need of more accurate battery SOC estimation techniques to reduce the range anxiety of EV users. The analysis also shows that if 20% of the slow charging capable EVs are replaced or modified with the DC fast charging capability, the existing EV charging infrastructure would be able to accommodate their charging power requirement without significant increase in peak charging demand. It has been observed that electricity price plays a major role in deciding the preference of charging stations among EV users. With implementation of higher peak hour pricing, 33.58% of EV charging load reduction has been observed at OCS.

The model developed in this thesis can be used for sizing ESS. It is demonstrated in chapter 3 with an example of OCS modelled with ABM having peak demand of 78 kW. With the on-site PV generation of 75kW peak, the ESS size was calculated as 419 kW. In the next application study, the agent environment was also linked with the modified IEEE 14-bus electrical network by solving the optimal power flow problem for an exemplar power system. For the spacial resolution of 92.16 sq. km, four charging stations with the peak charging load requirement of 236.13 kW, 326.52 kW, 232.15 kW and 284.97 kW were placed in the network. Buses 2, 3, 4 and 9 were having solar PV power

plants with capacities of 150 kW, 75 kW, 75 kW and 150 kW respectively. Buses 3 and 4 were having energy storage systems with capacities of 420 kW and 300 kW respectively. The OPF was run using this configuration and voltages were found to be within limits on all buses. Hence, the ABM presented in this study overcame various disadvantages inherent in existing models by accounting for the influence of human aggregate behaviour on the overall charging demand of EVs [115] and successfully demonstrated the possibility of extension of the proposed model for various power system studies. In future, the approach presented in this work can be validated using measured data from government agencies such as Singapore's Land Transport Authority or private charging station operators and EV fleet owners. Several important parameters were selected during this modelling process and are used for studying their effect on the individual and total charging demand at EV charging stations.

Chapter 4 presents a self-adaptive hybrid optimization algorithm which uses combination of deterministic and rule-based approaches for implementing energy storage management in the PV integrated EV charging station [116]. This part of the study emphasizes the application of the proposed ABM approach of EV charging loads in developing optimal power flow techniques for a charging station. The algorithm is flexible for adapting according to different EV charging models and various electricity price trends.

From the study, it can be observed that the proposed algorithm can effectively perform energy storage management between the ESS and the distribution grid, while continuously feeding private as well as commercial EV charging loads. It has resulted in saving of around 8.6% for charging stations serving private and commercial EVs. The study further analyzes the amount of the subsidy needed to economically deploy a PV system near an EV charging station along with ESS as the costs for PV and ESS are still rather high. The subsidy on the PV system to be provided by the government agencies is estimated with extensive simulation studies considering solar irradiation and LCOE of PV. Due to the higher cost of PV system, it has been observed that up to 40% subsidy is required on the PV system cost for the operation of charging stations catering to

privately owned EVs. This subsidy decreases drastically to 5% when the same charging station caters to commercial EVs. The reduction in subsidy requirement is due to the higher utilization of ESS in using TOU pricing. The reduction in cost of EV charging station operation depends on the distribution of loads throughout the day and volatility of the electricity market. Greater volatile market will earn more savings due to deployment of ESS using this approach.

Hence, with the proposed algorithm and realistic EV load modelling using ABM approach, ESS at the distribution side can become beneficial for economical deployment of a PV system near an EV charging station. Thus, ABM of EV charging has numerous possibilities for extension of results in the analysis of the effect of EV charging loads on the distribution system. This would eventually assist in designing policies for the high EV penetration in the distribution system, as demonstrated by the PV subsidy calculation.

However, ABM for EV charging used in this chapter also exhibits some limitations. The efficiency of the ABM is heavily dependent on the resource availability. The simulation of the microscopic model for EV charging behaviour requires large memory and it consumes more energy as well as computational resources. This limitation of microscopic ABM could be avoided by using the macroscopic model for ABM. The macroscopic model consumes lesser computational resources and requires less memory for its execution but the details to be observed are highly compromised. Hence, a proper balance of the microscopic level parameters and macroscopic level parameters has to be selected based on the application to be used for. The applications which do not require monitoring individual EV users such as unit commitment and generator placement studies can benefit from the macroscopic model. The models which require individual monitoring of EVs such as traffic congestion analysis, harmonic analysis of charging stations are required the detailed modelling of each EV. This consumes more time to execute model. Hence, the detailing of ABM to be used for EV charging applications depends on the application area and available computational resources.

5.2 Recommendations for future research

The future research directions for further investigating the methods and results presented in this thesis are as follow:

1. In this thesis, the ABM approach to predict the behavior of EV users under various scenarios is analyzed. Various parameters have been identified during this procedure of ABM and data in the context of Singapore is used for the modelling. In future, the proposed ABM approach can be combined with the real world data from the surveys and demographic projections obtained for other major cities such as San Francisco, Tokyo and London where high EV penetration is in progress. With the inclusion of the realistic data, the model would provide the charging demands under distribution system constraints.

The proposed ABM model could be extended by adding new parameters affecting EV user behavior such as road gradient, weather conditions and traffic conditions of the respective areas to study their influence on the total charging demand at charging stations. In the cold countries like Norway, Canada and Denmark, an EV battery inside EV is required to provide an energy heating along with the energy for driving. Moreover, the operation of lithium-ion batteries during the subzero temperature condition is another challenge. This will not only affect the output from the EV battery but also increase the frequency of charging thereby increasing charging load demand.

Such an extension of the model could be worked out for the optimum number and placement of the charging stations according to EV user behaviors. After deciding the numbers and placement of charging stations, the load flow studies can be undertaken to further analyze their impact on the distribution grid and better EV absorption into the system.

2. In this thesis, the hybrid optimization algorithm for implementing energy storage management in the PV integrated EV charging station is proposed. The proposed work can be extended by using a combination of the multiple ESS technologies

such as compressed air energy storage and vanadium redox-flow batteries. The use of only one type of ESS for EV charging load management applications may not provide optimum results. It may also put the stress on ESS if the performance characteristics of one type of ESS do not match with the dynamics of the EV charging load.

This can be solved using multiple technologies of ESS with different capacities according to their characteristics and suitability combined together. This combination allows for the utilization of each technology's advantages. Development of the control algorithm which will communicate with the converter of each ESS and performing the energy storage management for the whole system should be investigated for such Multi-Technology-Multi-Capacity ESS.

3. The proposed EV modelling approach in this thesis can be extended with the agent based peer to peer energy trading at the charging station. Here, an investigation on the feasibility of two-layer energy trading operation in reducing the electricity price paid by EV users would be a valuable addition to the EV charging domain. In the bottom layer of the peer to a peer energy trading, each EV user can be considered as peer. The charging station operator will receive the bids from the EV users and settle them upon arrival of the consensus.

After the settlement of all bids from the EV users, the charging station operator will evaluate the cost of operation for that time frame. This cost includes the cost of energy sold to EV users, cost of operation of ESS and cost of energy generated using the PC system. Based on this cost, each charging station in the distribution system will now submit their bid to the distribution system operator. Here, these charging station operators, other load users and energy producers will be considered as peers. Upon receiving the bids from all charging station operators as well as other energy producers and loads, the market operator will settle down the bid in the top layer of energy trading upon arrival of consensus [117].

All the peers in the top layer and bottom layer would act as agents. These agents would be taking their own decisions in bidding as well as consensus ar-

rival method based on their attributes. Such an agent based energy trading would help in decentralizing the electricity market and provides more consumer participation in the market. This method would thereby control the electricity prices for EV consumers according to consumer requirements assisting the grid to prepare towards high EV penetration.

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