Integration of electric vehicles into power grid

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INTEGRATION OF ELECTRIC VEHICLES INTO POWER GRID

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SUMMARY

Electric Vehicles (EVs) are becoming a promising solution to the environmental problems caused by the gasoline powered internal combustion engine automobiles. The major challenges to the deployment of EVs are high initial cost, limited range, increased peak demand, etc. But with good charging infrastructure which is integrated into smart grid, most of the disadvantages can be eliminated. Moreover, the EV batteries can be considered as distributed storage and used for various smart grid applications. For integration of EVs into smart grid, the requirements and feasibility of different charging methodologies for EVs are to be investigated. Based on the investigation, economic and efficient models for EV charging along with the associated charging strategies are to be derived for efficient integration. The impacts of different charging methods on battery life and distribution system peak demand are the two most important factors to be considered while deriving the models.

When the EVs are plugged into the grid for charging, all the operations including charging of their batteries and auxiliary functions such as grid support using Vehicle to Grid (V2G) and demand response management (DRM) are to be coordinated. This thesis presents a dynamic scheduling algorithm using novel priority criteria for integrating EVs into smart grid. The proposed dynamic scheduling algorithm is used for various other applications such as V2G capacity estimation and DRM. The scheduling algorithm is also used for verifying the methodology for estimating the number of EVs that can be supported by typical smart grid clusters with distributed energy resources. A novel data driven load model is used for determining the charging profiles of the EVs. Matlab based simulation models are developed to implement the proposed methods and illustrative case studies are used to evaluate the performance of the proposed system under a given set of conditions.

The proposed dynamic scheduling algorithm uses model based scheduling approach to overcome the disadvantages of existing scheduling methods. The load models used are stochastic building load demand (without EVs) and predicted EV charging profiles. Predicting the charging profiles of EVs connected to a building incorporated with a Building Energy Management System (BEMS) will improve the energy efficiency of the building. The predicted charging profiles along with the stochastic load data can be used

for calculating V2G capacity and for performing load/source scheduling. Data driven modeling has significant advantages in predicting the charging profiles of EVs, hence an Artificial Neural Network (ANN) based model is proposed for predicting the charging profiles of EVs connected to a building. The ANN model considers the previous charging profiles, initial State of Charge (SOC) and final SOC for predicting the charging profiles of EVs. Appropriate dynamic priority criteria required specifically for EV scheduling is also proposed. The algorithm is applied for both time coordinated EV charging and power coordinated EV charging. The objective function of the algorithm is to minimize the variance in priority values of the connected EVs. Minimizing the variance in priority values of the EVs will reduce the variations in fairness given to the EVs. The impact of different priority criteria and different combination of priority criteria on the fairness and chargeability of the EVs are also studied. Furthermore, the need for using weighted priority criteria is demonstrated.

The proposed dynamic scheduling algorithm is also applied to the real-time V2G capacity estimation for a group of vehicles. Using scheduling for V2G capacity estimation is a novel approach and has significant advantages. The V2G capacity that a group of vehicles can provide is estimated by evaluating the chargeability of the EVs to desired final SOC. Using scheduling for determining the V2G capacity will have a greater significance as the accuracy of the estimation is not affected by the time at which the estimation is carried out. A comparison of the proposed method with other methods which do not employ scheduling for the V2G capacity estimation is presented to demonstrate the advantages. The proposed dynamic scheduling algorithm is also applied for novel pre-emptive DRM of EVs in a building. The load shedding of the EVs is carried based on the priority values given by the proposed dynamic priority criteria. The chargeability of the EVs is ensured before deploying the EVs for DRM. The dynamic priority based pre-emptive DRM of EVs is implemented as part of intelligent pre-emptive DRM in a building which ensures that contracted capacity or demand limit (CC/DL) is not exceeded and at the same time reduction of energy consumption in the building is achieved.

A methodology which uses stochastic calculations (Monte-Carlo simulations) and linear programming for the estimating the optimal number of EVs that can be deployed under a high-rise building in Singapore is presented in this thesis. The proposed dynamic

scheduling algorithm is used to validate the accuracy of the estimation. Load demand data for five years and load model of EVs are used for the validation. Although there are various obstacles for the deployment of EVs, unavailability of charging infrastructure is the biggest obstacle. Hence, the cost-benefit analysis for installation of charging stations in buildings is also discussed by varying different parameters. It is important to ensure that the number of EVs integrated into the smart grid does not bring any adverse effect. A novel method for determining the limits based on the hot-spot temperature of distribution transformer is also proposed.

TABLE OF CONTENTS

ACKNOWLEDGEMENTS	I
SUMMARY	II
TABLE OF CONTENTS	V
LIST OF FIGURES	VIII
LIST OF TABLES	X
LISTS OF ACRONYMS AND NOTATIONS	XI
A. LIST OF ACRONYMS	XI
B. LIST OF NOTATIONS	XII
CHAPTER 1 INTRODUCTION	1
1.1 Introduction to Electric Vehicles	1
1.2 Introduction to Smart Grid Technology	2
1.3 Integration of EVs into Smart Grid	6
1.4 Research Motivations	10
1.5 Objectives of This Research Work	13
1.6 Contributions of This Research Work	14
1.7 Organization	16
CHAPTER 2 LITERATURE REVIEW	19
2.1 Electric Vehicles	19
2.2 Classification of EV charging	22
2.3 Smart/Coordinated Charging	25
2.4 Impacts of EV Charging on Power System	30
2.4.1 Impacts on Voltage Profile of Distribution System	31
2.4.2 Impacts on Power Demand and Power Losses	32
2.4.3 Impacts on Total Harmonic Distortion (THD)	34
2.4.4 Impacts on Life of Power System Equipment	35
2.4.5 Suitability of the Charging Strategies in Singapore's Context	36

2.5	Load Modeling for Determining EV Charging Demand	37
2.5.1	Artificial Neural Networks (ANNs)	40
2.5.2	Data-Driven Simulations	40
2.7	Demand Response	45
2.8	Summary	46
CHAPTER 3 PRIORITY BASED DYNAMIC EV CHARGE SCHEDULING		48
3.1	EV Charging Profile Prediction	48
3.1.1	Artificial Neural Network Model	50
3.1.2	EV Load Demand	53
3.2	Priority Criteria	55
3.3	Coordinated Charging	56
3.3.1	Power Coordinated Charging (PCC)	61
3.3.2	Time Coordinated Charging (TCC)	64
3.4	Impact of Priority Criteria on Chargeability and Fairness	65
3.4.1	Weighted Priority Criteria	73
3.5	Summary	77
CHAPTER 4 APPLICATIONS OF DYNAMIC EV SCHEDULING: VEHICLE TO GRID CAPACITY ESTIMATION AND DEMAND RESPONSE MANAGEMENT		78
4.1	V2G Capacity Estimation Method	78
4.1.1	Case Study 1: High-rise Residential Buildings	86
4.1.2	Case Study 2: Office Buildings	90
4.1.3	Comparative Analysis	96
4.2	Pre-emptive Demand Response Management	98
4.3	Summary	105
CHAPTER 5 A METHODOLOGY FOR OPTIMIZING THE NUMBER OF ELECTRIC VEHICLES DEPLOYED UNDER A SMART GRID		107
5.1	Introduction	107
5.2	Methodology for Estimating Optimal Number of EVs	109
5.2.1	Load Demand Data and Spare Energy Calculation	109

5.2.1.1	Load Demand Data and Stochastic Samples	109
5.2.1.2	Methodology for Spare Energy Calculation	110
5.2.2	Optimizing (maximizing) the Number of EVs	111
5.2.3	Validation of the Method Using EV Scheduling	115
5.3	Cost-Benefit Analysis	117
5.4	Determination of P^{limits}	118
5.4.1	P^{limit} Estimation based on Transformer LOL Calculation	121
5.5	Summary	123
CHAPTER 6 CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH		125
6.1	Conclusions	125
6.2	Recommendations for Future Research	127
REFERENCES		129
AUTHOR'S PUBLICATIONS		140
APPENDIX A		141

LIST OF FIGURES

Figure 1.1 Conventional Power Grid	5
Figure 1.2 Smart Grid.....	6
Figure 1.3 PV output power on a typical day.....	9
Figure 1.4 Wind turbine output power on a typical day.....	9
Figure 1.5 Availability of EVs	10
Figure 2.1 General structure of an EV car	20
Figure 2.2 Typical charging curves	21
Figure 2.3 Classification of EV charging.....	24
Figure 2.4 Typical load curves for dump, delayed and smart charging	25
Figure 2.5 Typical load curves of PCC and TCC	26
Figure 2.6 Charging curves of Renault Kangoo EV on different days	38
Figure 2.7 Functional diagram of DDM [87]	38
Figure 2.8 A typical structure of ANN.....	39
Figure 2.9 Model for data-driven simulations.....	42
Figure 3.1 ANN model used for predicting the charging profile of EVs.....	51
Figure 3.2 Result of prediction from ANN	53
Figure 3.3 Unscheduled load demand of an EV.....	54
Figure 3.4 Flowchart for the algorithm used in PCC	63
Figure 3.5 Flowchart for the algorithm used in TCC.....	65
Figure 3.6 Percentage failure for different EVs in PCC while using different priority criteria.....	69
Figure 3.7 Percentage failure for different EVs in TCC while using different priority criteria.....	70
Figure 4.1 Dynamic scheduling algorithm used for estimation of V2G capacity.....	81
Figure 4.2 Typical load curve and EV charging during off-peak period	81
Figure 4.3 Flowchart for V2G capacity estimation algorithm	83
Figure 4.4 (a) Estimation of V2G power and number of EVs for residential building; (b) Average current SOC and average required SOC	88
Figure 4.5 Peak shaving and valley filling with EVs	89
Figure 4.6 Predicted output of 70kWp solar PV system	91
Figure 4.7 Solar PV intermittency and V2G capacity.....	94

Figure 4.8 SOC profiles of EVs connected for V2G operation	94
Figure 4.9 Solar PV intermittency and V2G capacity under sudden solar PV loss	95
Figure 4.10 SOC profiles of EVs connected for V2G operation under sudden solar PV loss.....	96
Figure 4.11 Flowchart of algorithm used for determining the chargeability of EVs ...	100
Figure 4.12 Dynamic charge scheduling of EVs during low load period	104
Figure 4.13 Dynamic charge scheduling of EVs during high load period	105
Figure 5.1 A typical scaled down load demand with power limits	109
Figure 5.2 Flowchart of the algorithm used for calculating spare energy.....	112
Figure 5.3 Histogram of the difference between the desired final SOC and the estimated SOC at the time of departure for 5 years.....	116
Figure 5.4 Flowchart of the algorithm used for determining the power limits	121
Figure 5.5 Histogram of average temperature during the charging period	123

LIST OF TABLES

Table 1-1 Comparison of EV energy consumption with residential energy consumption	7
Table 2-1 Different types of EVs available in market [2]	19
Table 2-2 Characteristics of different batteries used in EVs	20
Table 2-3 Classification of EV charging stations based on their rated output power	22
Table 2-4 Difference between TCC and PCC	26
Table 2-5 Energy requirement of a typical EV	30
Table 3-1 Utility charges for buildings	60
Table 3-2 Overall probability of an EV not being charged with TCC and PCC	68
Table 3-3 Fairness Index before using Weights	71
Table 3-4 Fairness Index after using Weights	Error! Bookmark not defined.
Table 4-1 Typical EV Fleet of a HDB Building	87
Table 4-2 Typical EV Fleet of an Office Building	92
Table 4-3 Comparison of the Accuracy of V2G Estimation for Three Different Methods	97
Table 4-4 Comparison of V2G Estimation Accuracy	98
Table 4-5 Parameters for Dynamic EV Charge Scheduling	103
Table 5-1 Typical energy consumption of different types of EVs	113
Table 5-2 Spare energy available for different power limits	114
Table 5-3 Optimized number of vehicles	114
Table 5-4 Cost-benefit analysis for Case 1	117
Table 5-5 Transformer parameters	119
Table 5-6 P^{limit} with 1% additional LOL	122
Table 5-7 New P^{limit} after considering changes in ambient temperature	122

Lists of Acronyms and Notations

A. List of Acronyms

EVs	Electric Vehicles
GHG	Greenhouse Gasses
SES	Smart Energy Storage
DERs	Distributed Energy Resources
PV	Photovoltaic
THD	Total Harmonic Distortion
NTU	Nanyang Technical University
TCC	Time Coordinated Charging
PCC	Power Coordinated Charging
LLF	Least Laxity First
EDF	Earliest Deadline First
RESs	Renewable Energy Sources
V2G	Vehicle to Grid
DRM	Demand Response Management
APC	Achievable Power Capacity
CPC	Contracted Power Capacity
SOC	State of Charge
DG	Distributed Generation
DDM	Data Driven Modeling
ANN	Artificial Neural Networks
DR	Demand Response
MAPE	Mean Absolute Percentage Error
HDB	Housing development Board
EMA	Energy Market Authority
SP	Singapore Power
LTA	Land transport Authority of Singapore
CPS	EV charging power schedule (CPS)
CTS/CS	Charging Time Schedule/ Charging Schedule (CTS/CS)

BEMS	Building Energy Management System
CC/DL	Contracted Capacity/ Demand Limit
LOL	Loss of Life
iid	Independent and Identically Distributed random samples
AC	Air Conditioner
VSD	Variable Speed Drive
ILs	Interruptible loads

B. List of Notations

P_{actual}^n	The actual power required
P_{cc1}	Power demand during constant current region
W	A pseudo-random integer
SOC_{new}	Incremented SOC due to the power supplied during the previous one minute duration
SOC_{old}	The previous minute SOC
P_{1c}	The power requirement for charging the battery at the rate of 1C
P_{slope}	decrement using time required for constant voltage region
X_i	The power consumed by the EV at given instant and i represent the previous charging profile's id
C_f	the output which is compared with target output (the latest charging profile).
V_{ij}	The weight between input and hidden layer,
$W_{i,k}$	The weight between hidden and output layer,
θ_j	The constant bias used with V_{ij} .
γ_j	The constant bias used with $W_{i,j}$
δ_{t+m}	The relative incremental of the actual load at time $(t+m)$
L_{t+m}	The actual load at time $(t+m)$,
L_t	The actual load at time t and
m	The lead time of the forecast.

C_f	The output which is compared with target output
b_f	The input to hidden layer
$\hat{\delta}_{t+m}$	The forecasted relative incremental of the actual power
$\hat{L}_{t+m}$	The forecast power at time $(t+m)$
n	The total number of samples
P_F	The forecasted power,
P_A	The actual power.
$p_j^{uEV,i}$	Unscheduled total demand of EVs can be obtained ,
$p_l^{EV,i}$	Charging profile of i^{th}
m_i	The departure interval of i^{th} EV ,
k_i	The total number of intervals required for charging the i^{th} EV
m_{max}	The interval in which the last EV departs
σ_{max}	The formula to select the departure interval of the last EV to depart
α_i^1	The priority criterion based on SOC of EV battery
α_i^2	The priority criterion based on slack time available for
α_i^3	The priority criterion based on time/energy already allotted for the EV
$N_{dep,i}$	The number of half-hour time intervals from current time to departure time for the i^{th} EV.
$N_{req,i}$	The minimum number of half-hour time intervals required for charging the i^{th} EV up to the desired SOC.
$N_{total,i}$	The equivalent number of half-hour time intervals required for charging EV from initial to desired SOC.
$E_{sup,i}$	The energy supplied to the i^{th} EV
$E_{total,i}$	The energy required to charge the EV from the initial SOC to the desired SOC.
$N_{com,i}$	The equivalent number of half-hour time intervals used for charging the i^{th} EV

$p_j^{loaddemand}$	Load demand of buildings/smart grid without EVs
$p_{x,j}^{resunit}$	Load demand of individual residential unit
$\mu_{x,j}$	The mean of the load demand of individual unit
$\sigma_{x,j}^2$	The variance of the load demand of individual unit
$pdf_{x,j}$	The and probability density function of the load demand of individual unit
'x'	The residential unit number
'j'	Half-hour interval
p^{limit}	The power limit for ensuring that the EV load demand does not exceed a predetermined value
p_j^{uEV}	The sum of all $p_j^{uEV,i}$
P_{CC}	Contracted capacity/ maximum power demand limit/ power demand constraint
$p_j^{avaible}$	The power available for EV charging
$CPS_{n,48}$	Charging power schedule for n EVs
$P_{i,j}$	The power allotted to the i^{th} EV for charging its battery on the j^{th} half-hour interval
$P_{EV,i}^{max}$	The maximum power limit based on the power handling capabilities of the EV charger
$P_{EV,i}^{min}$	The minimum power limit based on the power handling capabilities of the EV charger
ρ_i	Priority value
$E_{req,i}$	The minimum energy required for charging the i^{th} EV up to the desired SOC
$CTS_{n,48}$	Charging power schedule for n EVs
$x_{i,j}$	The control signal broadcasted to EV chargers
FI_i	Fairness index value
$N_{F,i}$	The number of failures of the i^{th} EV
N_{FT}	The total number of failures of all EVs

$E_{R,i}$	The average energy requirement of the i^{th} EV
w_i	The weight given to each priority criterion
p_j^L	Same as $p_j^{loaddemand}$
$p_i^{EV,i}$	Predicted EV charging profile
p_j^{RES}	Predicted output of RESs
$n_j^{EV,i}$	Number of allotted charging intervals for each $EV_{lapsed,j,i}$ EV.
k	The total number of charging intervals required for charging a particular EV
i	EV number
n	The total number of EVs.
p_j^{TD}	Total demand after adding EV load demand
p_i^{v2gmax}	Maximum V2G power
$p_i^{v2gcont}$	Continuous V2G power
$E_i^{v2gav'lable}$	V2G energy available from each EV
$SOC_i^{current}$	Current state of charge,
SOC_i^{final}	Desired final state of charge
SOC_i^{min}	Minimum required state of charge
χ_i	The priority parameter due to V2G power/energy supplied by the EV
$N_{v2g,i}$	The equivalent number of half-hour time intervals during which The EV is supplying power.
$N_{total,i}$	The equivalent number of half-hour time intervals required for charging EV from initial to desired SOC
E_i^{v2gmax}	Maximum V2G energy available from each EV
τ	Time interval considered for V2G operation
C_i	Battery capacity of i^{th} EV
$E_i^{v2gav'lable}$	Actual V2G energy available from each EV

τ_l	The actual time for which the V2G power is supplied or can be supplied during the given interval.
p_i^{v2g}	Actual V2G power available from each EV
$E^{v2g total}$	Total V2G energy available from all EVs
$p_j^{v2g total}$	Total V2G power available from all EVs
$p^{ave\ pv}$	Average solar PV output
$p_j^{act\ pv}$	The actual solar PV output
$p_j^{v2g\ required}$	V2G power required during the intervals j
Cd_n	Chargeability matrix for EVs
$SOC_i^{m_i}$	State of charge in the interval m_i
P_{CD}	Building current load demand
$\sigma_{\min}(\rho_{i,j})$	The selection process of the EV having the lowest priority values
$\sigma_{\max}(\rho_{i,j})$	The selection process of the EV having the highest priority values
p_n	The load demand for any given day
p_i	The load demand for i^{th} interval ($i=1, 2, 3, \dots, 48$).
$\overline{p_i}$	The mean from load demands
$\overline{\sigma_i^2}$	The variance from load demands
N	The number of samples generated
p_i^k	The k^{th} iid
σ_i^2	The variance of generated samples
E_{spare}	Spare energy available
a_i	The number of vehicles for each type
x_i	The average energy required for the corresponding type of vehicles
k_i	The percentage of each type of vehicle
n	Number of vehicle types
C_i	Cost per kWh for each category of vehicle.
F_{EQA}	F_{EQA} The equivalent aging factor for the total time period

n	Index of the time interval, t
N	Total number of time intervals
$F_{AA,n}$	Aging acceleration factor for the temperature which exists during the time interval t_n
t_n	Time interval in hours,
Θ_H	The winding hotspot temperature, °C.

CHAPTER 1 INTRODUCTION

An introduction to Electric Vehicles (EVs) and their integration into smart grids are presented in this chapter. The research motivations, objectives, contributions and organization of this thesis are also discussed in this chapter.

1.1 Introduction to Electric Vehicles

The invention of electric locomotives, both battery powered EVs and rail powered EVs can be dated back to 1835 [1]. Interestingly in the beginning of the 20th century, EVs had the majority of market share in commercial automobiles. However, with rapid advancements in the internal combustion engine, wide availability of cheap fossil fuels and limitations in battery technology, the preference for using EVs with onboard energy storage slowly faded away. However, rail powered and overhead line power EVs such as trams, trains and even buses which are significant for public transportation remained in use. The 1973 oil crisis forced the governments across the world to consider alternatives for fossil fuel powered vehicles. Transportation sector is an important source of greenhouse gasses (GHG). Conversion of conventional internal combustion engine vehicles to EVs helps in decreasing GHG emissions of the transportation sector. With the subsequent increase of awareness on the detrimental impact of fossil fuels on environment, the resurgence of the EVs with onboard energy storage became inevitable. Furthermore, the accelerated innovation in battery technology made the launch of EVs feasible both technologically and economically.

Currently, all the leading automobile manufacturers have launched prototypes and concept EVs [2]-[4]. Conversion of conventional fossil fuel powered vehicles to EVs is considered as one of the best solution to decrease the emissions of transportation sector and increase the efficiency of transportation system. EVs are not only used for personal transportation application but also there are several other applications such as electric buses for public transportation, electric forklifts in industries and autonomous vehicles for hazardous environment. Apart from battery operated EVs, there are few other types of EVs such as fuel cell vehicles, super-capacitor vehicles and on-line EVs. Significant

advantages of EVs compared to their internal combustion engine counterparts are as follows

1. Zero-tail pipe emission, hence higher degree of control on air pollution.
2. Higher efficiency in urban areas due to feasibility of regenerative braking.
3. Quite operation due to lesser moving parts.

Whereas limited range, long refueling time and high initial cost are the disadvantages. Apart from the above obstacles, unavailability of charging infrastructure is also a biggest obstacle which hinders the deployment of EVs. Even the most willing environment enthusiasts are discouraged because of the unavailability of proper charging infrastructure. In Singapore, the government has initiated a \$1 billion sustainable-development blueprint to build a greener, more energy efficient and sustainable nation [5]. Furthermore, Singapore has also set aggressive transport energy efficiency goals and also has a targeted National Climate Change Policy to increase the deployment of EVs to meet transportation needs of its citizens [6]. With many such government initiated programs that incentivize the purchase of EVs, more EVs are expected to be connected to the power grid.

Apart from serving the main function for transportation, EVs also have additional auxiliary functions. EV batteries when aggregated can be treated as large smart energy storage (SES) and can be used to reduce the size of energy storage required for distributed energy resources (DERs), and for frequency regulation and voltage regulation. Such auxiliary functions will help EV owners to reduce the operation cost as well as mitigate the issues related with integration of EVs into power grid.

1.2 Introduction to Smart Grid Technology

The ever increasing global electrical energy demand requires sustainable electricity generation options. The rapid urbanization across the world with increasing population and demand for a better quality of living has led to a greater usage of energy. However, continuously increasing the capacity of central power grid is not feasible in all the cases. This has resulted in escalating pressure on the use of available resources that are mostly fossil fuels in the form of coal, oil and gas, which have also led to uncontrollable rise in air pollution. For instance, approximately 31% of the total electricity consumption in

Singapore is used by buildings [7]. DERs such as solar photovoltaic (PV) panels, wind turbines, fuel cells, combined heat and power plants help in mitigating such issues. However, these DERs are to be properly integrated to avoid any stability problems as well as the intermittency issues associated with some of the DERs which are renewable energy sources. Instead of increasing the energy production from traditional carbon based sources to meet the growing demand, managing and controlling the energy utilized by buildings can also lower the energy consumption. Furthermore, this will help reduce the impact of rising energy costs and lead to savings in electricity bills. With the advent of information technology, it is not only possible for integration of DERs but also possible to have the loads respond to the commands.

Smart metering is generally carried out using an electronic meter which can record the energy consumption in various time intervals with resolution ranging from few minutes to one hour. In smart metering the electronic meter also has the capability to communicate the recorded information with utility for the purpose of monitoring and billing. Furthermore, the meters also have the capability of two-way communication between the meter and the central system. Such a feature is different from traditional meter reading and provides feasibility for control of load demands at remote locations. Smart metering is a subset of smart grid.

The basic concept of smart grid technology is to integrate monitoring, control, analysis and two-way real-time communication to the electric transmission and distribution systems to improve efficiency of the systems while reducing the energy consumption. The smart grid will allow utilities to distribute electricity around the system as efficiently and economically as possible. It will also allow and encourage the consumers to use electricity as economically as possible while reducing consumption. The smart grid actually builds on many of the technologies currently employed by utilities but includes communication and control capabilities that will optimize the operation of the entire electrical grid. The smart grid is also positioned to take advantage of new technologies, such as distributed generation technologies, plug-in hybrid electric vehicles, supply side management, demand side management, home and building energy management systems, and many more.

Smart grid is a digital superstructure employing information networking technology to embed processing and communications into the existing power grid. Smart grid enables the power grid to become more observable, controllable, automated and integrated. The smart grid technology enables the utilities to have a distributed system which can be integrated via the information technology. Smart grid technology allows consumers to participate directly or indirectly in the consumption as well as generation of energy. Hence the scenario will be such that where load follows generation rather than the other way around. In short, a power grid network which is distributed and consumer interactive but not a centralized and producer-controlled network is called as smart grid.

The major features of smart grid are:

1. It facilitates two-way real-time communication between electric transmission and distribution system
2. It facilitates monitoring, control and analysis for whole network including the consumer loads.
3. It improves the efficiency while reducing the energy consumption [8].
4. It utilizes existing facilities of utilities over which communication and control capabilities that can optimize the operation of the entire electrical grid are added.
5. It has capability to take advantage of new technologies, such as distributed generation, EVs, demand side management and home/building energy management systems.

The demand side management aspect of smart grid is an interesting concept as it can provide various advantages. With the communication infrastructure capable of monitoring and controlling the loads, many power system stability control options can be executed efficiently and effectively. For example, up regulation and down regulation for frequency stability can be executed by load shedding and adding load respectively. Virtual Power Plant is an advanced concept of using such controllable loads to create a virtual generator/load that could be used for regulation and various other power system operations. EVs are important part of the demand side management in smart grids. A number of smart grid projects have already been completed and many are on-going around the world. Few such projects are listed below

1. The Energy Market Authority (EMA) of Singapore's "Intelligent Energy System (IES)" [9].

2. Telegestore project in Italy was the first and largest smart grid installed with a budget of US\$2.87 billion [10].
3. Smart grid development in the city of Austin, Texas, USA was started in 2003 and the first phase of the project was completed in August 2008 [11].
4. The State Grid Corporation of China (SGCC) started a large-scale project from 2007 for the development of a smart grid system [12].

The direction of power flow in conventional power grid and smart grid is depicted in Figures 1.1 and 1.2 respectively. Figure 1.1 shows the schematic diagram of the conventional distribution system where the real and reactive power flows radially from the higher to the lower voltage levels. When there is a significant penetration of DG units in the existing distribution network, as shown in Figure 1.2, the flows of real and reactive power may become reversed, transforming the present passive distribution network into an active network with power flows and voltages determined by the generation and the loads. The change of the real and reactive power flows will therefore result in many problems since the DG units do not behave in the same way as conventional loads. As EVs can also act as an energy source while using them in vehicle to grid applications, all the issues associated with the penetration of DG units will be applicable for EVs as well. However, such issues are not focused in this thesis.

Figure 1.1 Conventional Power Grid

Figure 1.2 Smart Grid

1.3 Integration of EVs into Smart Grid

EV integration into the grid requires proper attention to avoid unnecessary complications. The energy requirement of a car is compared with the average residential energy consumption in Singapore [13] in Table 1-1. Although addition of EV load demand per unit seems to increase the overall load demand by 71.8%, it is not the case with high-rise residential buildings. This is due to the fact that not all occupants in the high-rise residential buildings will own a car (hence not applicable for EV adoption). Taking into consideration number of personal cars per 1000 people in Singapore [14] and a typical smart grid (450 residential units), the number of EVs (with 100% penetration) would be 45. Calculating the energy requirement of 45 EVs and comparing it with the total energy consumption of all units, the increase in energy demand is 8% for 24 hours. However, according to literature the EVs have to be charged during off-peak period to avoid any significant impact on power system. Hence majority of the charging happens during the off-peak period, i.e., between 22:00 hours to 06:00 hours (considering 8 hour charging period). Hence, when 8% of the total energy has to be supplied in 8 hours (i.e., 1/3rd of 24 hours), the overall power demand during charging period increases by 24%. And if 6 hours charging period is considered, the overall power demand during charging period increases by 32%.

EVs behave like a flexible load, however they will have significant impact on the power system and has the potential to increase peak load of the power system if not managed properly [15]-[17]. Furthermore, if the problems are not addressed properly, it will result in decrease in power quality and increase in operation cost for the peak demand. Hence to improve the power quality of the system, the problems should be properly addressed.

Table 1-1 Comparison of EV energy consumption with residential energy consumption

Average energy required/km in kWh	0.2006
Average km/day (for Singapore)	55
Average energy required/day in kWh	11.00
Increase in average residential energy consumption (in %) with use of EV (average residential energy consumption =15.33kWh)	71.8

The problems associated with the large-scale penetration of EVs are as follows:

- a) **Unpredictable increase in peak demand:** The unpredictable charging of the EVs due to various mobility patterns of EV users will result in an unpredictable increase in peak demand. The uncertainty in the arrival of EVs is the main cause of this problem [17]. The various charging strategies available in literatures to mitigate this problem focus mainly on personal vehicles parked at individual houses and small buildings [15]-[20]. Such strategies are not suitable for urban cities where 70%-80% of the buildings are high-rise multi-storey buildings.
- b) **Voltage fluctuations and increased total harmonic distortion:** EV charging involves the conversion of power through power electronic devices which will result in increased voltage fluctuations, harmonic distortions and power losses. The problems will be more serious if charging happens during peak demand [18]. All the methods available in literatures primarily focus on shifting the charging demand from peak period to off-peak period in order to reduce the problems related with EV charging. However, such an approach will not ensure an optimal solution to these problems. The increased power losses and total harmonic distortion (THD) problems associated with different battery charging modes must also be considered.

- c) **Impacts on life of power system equipment:** EV charging has serious impact on the life of transformers and cables [16] due to the increase in peak demand due to addition of EVs. The life of both transformers and cables depend on the hot-spot temperature. The increased THD also has a cascading detrimental effect on the life of transformers and cables.

Various analyses on the impact of EV charging show that uncoordinated charging of EVs will result in detrimental impacts on the power system operation [16], [21] and [22]. However, if the EV charging/discharging is managed properly, it is not only possible to mitigate these problems but also possible to derive many auxiliary functions such as distributed reserves for renewable energy [23]-[25]. For utilizing the EVs for auxiliary functions, the availability of the EVs should be considered. The availability of EVs can be obtained from the travelling patterns of different types of EVs. EVs have travelling ranges usually between 90km to 160km, which is well within the average travel distance in urban cities.

Figures 1.3 and 1.4 show the typical daily curves of the output power from a solar PV system [26] and a wind energy system [27] respectively. As shown in Figures 1.3 and 1.4, both PV and wind energy systems are intermittent in their generation and have very distinct generation characteristics from each other. It can be observed from Figure 1.3 that a solar PV system typically generates power between 07:30 to 19:00 hours. Thus, EVs which are usually immobile from 10:00 to 16:00 hours can be utilized to compensate for the variability in the power generated by the solar PV system. On the contrary, as shown in Figure 1.4, a wind energy system has a higher power generation during night time from 19:00 to 6:00 hours which also corresponds to off-peak periods of energy consumption. During this period, there might be surplus energy generated from the wind energy system. In this case, the role of EVs is reversed and can function as storage devices to store the surplus energy generated by the wind energy system.

Figure 1.3 PV output power on a typical day

Figure 1.4 Wind turbine output power on a typical day

The availability of EVs has an inherent variability but it can be predicted to a certain level of accuracy which makes EVs highly suitable for being utilized as SES. Based on research conducted by the authors in [15], [28]-[30], it was found that most EVs are immobile for 90% of the time in a day. The time during which the EVs are immobile and available to be used as SES is shown in Figure 1.5.

Figure 1.5 Availability of EVs

It can be observed that majority of the EVs are generally used for transportation to and from workplace between 08:00 to 10:00 hours and 16:00 to 20:00 hours respectively. These are the time periods when the EV availability for auxiliary functions is low. However, during peak hours (i.e., between 10:00 and 14:00 hours) and off-peak hours (i.e., between 22:00 and 05:00 hours) the EVs are usually not used or immobile as they are typically plugged in for charging at the workplace and home car park respectively. These are the time periods when the EV availability for auxiliary functions is high.

1.4 Research Motivations

Market penetration of EVs continues to gain momentum, as the move is towards increasingly distributed, clean and renewable electricity sources. EV charging shifts a significant portion of transportation energy to the building electricity meters. Hence, integration strategies for energy-efficiency in buildings and transport sectors are of critical importance for the future of transport. Improving energy efficiency in buildings and transportation, which together constitute two-thirds of energy end-use in most of the countries, has traditionally followed parallel strategies [31]. However, that situation needs to change. In highly-urbanized cities like Singapore, transportation accounts for a

significant percent of the total emissions, for instance transportation contributes 19% to the total emissions [32].

The California Air Resources Board's Jan 2012 Report stipulates that by 2025, 15% of all new cars and trucks sold will be powered by batteries, hydrogen fuel cells, or other technology that emits little or no air pollution. EVs have the greatest potential for widespread market penetration and the literature indicates that the EV charging will predominantly occur at buildings and homes during off-peak hours [33]. Similarly, the rapid urbanization with increasing population and demand for a better quality of living has led to a greater usage of energy. Singapore being a highly urbanized country, 17% of the total energy was consumed by buildings [7]. Analysis presented in [34] shows that EVs will increase residential building energy loads by 13% and electricity use by 55% for a 2010 typical home.

The additional load implications will adversely affect building energy targets such as Singapore's sustainable-development blueprint, which aims to build a greener, more energy efficient and sustainable nation [5]. On the other hand, effective management of EVs in conjunction with the grid could have mutually beneficial impacts. It is estimated by the International Energy Agency (IEA) that electrified transport could reduce greenhouse gas emissions by 30% around the world by 2050.

Singapore's hot tropical climate, lack of natural resources and expanding economy pose interesting energy challenges. There were about 0.95 million motorized vehicles in Singapore at the end of 2012 [14]. Singapore is actively considering deployment of EVs and launched its EV test-bed program in June 2011. The test-bed program aims to evaluate the feasibility and advantages of adopting EVs in Singapore. This program incentivizes purchase of EVs through the Enhanced Transport Technology Innovation and Development Scheme (TIDES+), which allows a waiver on all vehicular taxes for the test-bed participant, making the EV 50-60% cheaper. In return, the participant is obligated to provide basic information regarding the EV and the current trip through a smart device located within the EV.

EVs have ranges usually between 90km to 160km, which is well within limit of the average travel distances of 55km in Singapore [14]. In Singapore, natural gas is

predominantly used for electricity generation; consequently it is estimated that the overall emissions reduced by 66% when a gasoline car is converted to an equivalent-size EV [35]. Singapore is also actively examining renewable energy resources such as solar energy to diversify its fuel mix and also reduce environmental impact. This reinforces the need to closely examine and deploy EVs in Singapore. As part of the EV test-bed program, Bosch is contracted to take up design, development and deployment of EV charging stations both slow (full charge within 7-8 hours) and fast (full charge within 30-45 minutes). With the increase in deployment of EVs, the charging infrastructure will also be scaled up.

Nanyang Technical University (NTU) is one of Singapore's largest public universities with a campus of 200 hectares area, with 30,000 students and 6,000 faculty and staff. NTU announced its Campus Master Plan in February 2011, whereby it established its intention to become a mini-city, with adoption of energy efficient and sustainable technologies. This possibly includes provisions for EVs (electric buses, cars and bikes) for transportation. Electrification of transportation will significantly reduce the amount of greenhouse gas emitted on campus and also improve the efficiency of the transportation sector dramatically.

Many countries including Singapore have taken strong steps for increasing the deployment of EVs targeted towards the improvement of national environmental condition [6]. However, large-scale penetration of EVs that behave like flexible loads will have significant impact on the power system and the potential to increase peak load demand if not managed properly. Large-scale penetration of EVs will result in other problems such as unpredictable increase in peak demand, voltage fluctuations and increased total harmonic distortion. If the EVs are managed properly it is not only possible to mitigate the problems but also possible to derive many auxiliary functions such as distributed reserves for renewable energy. Hence a structured implementation of EVs has the potential to decrease the power system operation cost as well as increase the reliability and stability of the power system. Instead of increasing the energy production from traditional carbon based sources to meet the growing demand, managing and controlling the energy will ensure lower overall demand and consumption of energy.

Onset of smart grid will provide an extensive data which was unavailable earlier via the smart meters and information technology. The available data has to be used effectively

to obtain the maximum benefit of the implemented technology. Hence, data driven simulations for studying the performance of different of EV deployment strategies are an attractive option. Data-driven simulations offer a wide variety of advantages. Updating the model parameters to account for the changes due to ageing is one of the major advantages. Furthermore, scaling up the system to account for new additions is relatively simple. The effectiveness of data-driven simulations and controller design using data-driven modeling has been demonstrated in [36]-[39]. Hence the motivation is to study the application of data-driven simulations which can facilitate smooth integration of EVs into smart grid such that the benefits of EVs can be realized effectively.

1.5 Objectives of This Research Work

There are many research works available in literature which analyses the impacts of EV charging on the existing power system. The analyses on EV charging methods clearly illustrate that un-coordinated charging of EVs is detrimental to the overall power system operation [16], [21] and [22]. Coordinated charging which is also known as smart charging is the superior method for charging EVs with minimal impact on the power system operation. Coordinated EV charging can be broadly classified into two types, i.e., time coordinated charging (TCC) and power coordinated charging (PCC). Scheduling of EV charging is the vital component of coordinated EV charging methods.

The primary objective of this research is to develop dynamic co-ordinated charging algorithms (dynamic real-time scheduling algorithms) and apply the algorithms for determining the auxiliary functions of EVs. Appropriate choice of priority criteria is essential for robust performance of the EV scheduling algorithm. Furthermore, the customer's satisfaction achieved using traditional and modified robust dynamic scheduling algorithms [40]-[43] can be enhanced using proper combination of priority criteria. Hence the next objective is to analyze the impact of each priority criterion as well as the impact of various combinations of different priority criteria on the chargeability of the EV to the required state of charge (SOC) and fairness in the allocation of charging time. Evaluation for the need of using weighted priority criteria for scheduling EV charging along with optimal weights required for different cases is also carried out.

Using scheduling for determining the auxiliary functions of EVs has significant advantages. An aggregated number of EVs provide a platform for SES in buildings which can be used during periods of maximum demand or high electricity price as well as for leveling the intermittent outputs of renewable energy sources (RESs). However, the vehicle to grid (V2G) capacity varies over time based on the availability of the EVs and their individual SOC. Hence a real-time V2G capacity estimation is important for utilizing EVs as SES efficiently. In this research, the objective is to develop an algorithm for half-hourly V2G capacity estimation using real-time EV scheduling. Similarly the EVs act as flexible load which can be used for demand response management also. This research aims to develop an intelligent preemptive demand response management (DRM) for EVs using dynamic EV charge scheduling.

Finally, a methodology is proposed for the estimation of the optimal number of EVs that can be deployed under a given smart grid. Monte-carlo simulations and linear programming are used for the estimation. The methodology is applied to calculate the optimal number of EVs that can be deployed under a high-rise building in Singapore. The method is validated using load demand data of five years, load model of EVs and EV load scheduling. The cost-benefit analysis for the installation of charging stations in buildings is also discussed by varying different parameters. As a final step the limits required for scheduling the EVs are obtained from a methodology which determines them based on transformer's loss of life.

1.6 Contributions of This Research Work

The main contributions of this research are as follows:

- i. A dynamic priority based real-time scheduling algorithm is proposed in [44]. The dynamic scheduling algorithm proposed in this research uses a data-driven model based approach to overcome the disadvantages of existing scheduling methods. The algorithm is proposed for time coordinated charging and further extended to power coordinated charging in [45]. Appropriate choice of priority criteria is essential for robust performance of the EV scheduling algorithm. Furthermore, the customer's satisfaction achieved using traditional and modified robust dynamic scheduling algorithms can be enhanced using proper combination of priority

criteria. Hence in this research analysis on the impact of each priority criterion as well as the impact of various combinations of different priority criteria on the chargeability of the EV to the required SOC and fairness in the allocation of charging time is carried out. The need for using weighted priority criteria for scheduling EV charging is also evaluated and the impact of using optimal weights required for different cases is also presented. The analysis can serve as a guideline while selecting different parameters as priority criteria for any scheduling algorithm. A new approach for determining the load demand of EVs based on previous charging profiles is also introduced in [46]. The aging process of the battery, which depends on equivalent number of charging cycles the battery has undergone can be captured easily with the proposed method.

- ii. The estimation of real-time V2G capacity of EVs is crucial for using EVs as distributed energy storage. A novel algorithm for half-hourly V2G capacity estimation using real-time dynamic EV scheduling is proposed [44]. The proposed V2G estimation method is also compared with the fixed minimum SOC limited estimation method and plug-in probability based estimation methods which do not employ scheduling of EVs. It is observed that the proposed method can improve the accuracy of V2G estimation and is not affected by the time remaining before departure. An intelligent preemptive DRM using dynamic EV charge scheduling is proposed [47]. The dynamic priority based on appropriate priority criteria is used for DRM of EVs and the chargeability of EVs is ensured before deploying the EVs for DRM.
- iii. A methodology is proposed for the estimation of the optimal number of EVs that can be deployed under a given smart grid [48]. Monte-carlo simulations and linear programming are used for the estimation. The methodology is applied to calculate the optimal number of EVs that can be deployed under a high-rise building in Singapore. The method is validated using load demand data of five years, data-driven load model of EVs and EV load scheduling. The cost-benefit analysis for the installation of charging stations in buildings is also discussed by varying different parameters. A methodology for determining the limits required for the previous step is proposed, and it estimates additional power that a distribution transformer can supply for the integration of EVs with a predefined additional loss

of life [49]. The above method is useful for determining the limits for scheduling of EVs.

1.7 Organization

This report consists of six chapters and which are listed below:

Chapter 1: Introduction

In this chapter, basic information about electric vehicles, smart grid technology and integration of electric vehicles into smart grid is discussed. The motivations, objectives and contributions of the research work along with the organization of this thesis are also discussed in this chapter.

Chapter 2: Literature Review

In Chapter 2, a literature review of previous and present research works on the impact of integrating electric vehicles into smart grid is given. The review of methodologies used for circumventing the issues associated with integration of electric vehicles into the existing smart grid is discussed. The research works on different charging strategies, vehicle to grid energy transfer and demand response with EVs are also discussed.

Chapter 3: Priority Based Dynamic EV Charge Scheduling

In Chapter 3, a new approach for determining the load demand of EVs based on previous charging profiles is introduced. A dynamic scheduling algorithm which uses model based scheduling approach is presented. The algorithm is used to develop both time coordinated charging and power coordinated charging. Appropriate priority criteria essential for robust performance of the EV scheduling algorithm is presented and the overall performances of both EV charging methods employing various combinations of different priority criteria are evaluated using data-driven simulations and the results are discussed. The necessity for using weighted priority criteria is also studied and the improvement in

the performance of the algorithm while using appropriate weights is also presented in this chapter.

Chapter 4: EV Scheduling Driven Vehicle to Grid Capacity Estimation and Demand Response Management

In this chapter, the dynamic scheduling algorithm developed in Chapter 3 is employed to develop an algorithm for half-hourly V2G capacity estimation. The algorithm is applied to different cases such as residential high rise buildings and commercial high rise buildings. The results are presented for cases studies. The proposed V2G estimation method is also compared with the fixed minimum SOC limited estimation method and plug-in probability based estimation methods which do not employ scheduling of EVs for estimating V2G capacity. The dynamic scheduling algorithm is also applied for developing an intelligent preemptive demand response management using EVs. Simulation results for the performance of the algorithm implemented in a building energy management system are also presented.

Chapter 5: A Methodology for Optimizing the Number of Electric Vehicles Deployed Under a Smart Grid

In chapter 5, a methodology for estimating the optimal number of EVs that can be deployed under a smart grid is proposed. Stochastic samples and Monte-Carlo simulations are used for estimating the spare energy available. The proposed method is applied to a typical case study and the expected spare energy available is calculated by varying the power limits during the charging period. The estimation is carried out for a period of five years and the results are tabulated. The optimized number of EVs is determined for average expected spare energy of five years. The constraints for optimization are also varied and the corresponding results are listed. The proposed method is validated using dynamic scheduling and load models of EVs proposed in Chapter 3. The chargeability of the vehicles to the desired SOC is verified for a period of five years in the validation process. A cost-benefit analysis is also discussed for one particular case. A methodology for estimating additional power that a distribution transformer can supply for the integration of EVs with a predefined additional loss of life

is presented. This method can be used for determining the limits required for EV scheduling in this research.

Chapter 6: Conclusions and Recommendations for Future Research

In this chapter, the overall assessment of this research work as well as the proposed future work is presented.

CHAPTER 2 LITERATURE REVIEW

In this chapter, a literature review on the EVs, classification of EV charging, smart/coordinated charging, impacts of EV charging on power system, load modeling for EVs, V2G and DRM of EVs are presented.

2.1 Electric Vehicles

EVs for personal transportation are an important part of the EV penetration. A typical structure of EVs used for personal transportation is shown in Figure 2.1. When the EVs are integrated into the power grid, the EV batteries are connected to the power grid through an onboard AC/DC power converter. The power rating of these converters varies from 1.6kW to 14.4kW [50]-[52]. The driving range of these EVs depends on the energy capacity of the batteries used and the type of vehicle. The range of energy capacity of the EVs is between 7kWh and 85kWh [2]. Table 2-1 categorizes different commercially available EV models based on the energy capacity of their batteries. There are also many EV motorcycles and EV bicycles commercially available [3]-[4].

Table 2-1 Different types of EVs available in market [2]

Battery capacity category	Energy capacity (E)	Models
Low	$E \leq 16\text{kWh}$	Renault Twizy, REVAi, Buddy, Mitsubishi i MiEV and Mia electric.
Medium	$16\text{kWh} > E < 30\text{kWh}$	Nissan Leaf, Smart ED, Renault Fluence Z.E., Ford Focus Electric, Honda Fit EV, Renault Zoe, Roewe E50 and Mahindra e2o.
High	$30\text{kWh} \geq E < 45\text{kWh}$	Wheego Whip LiFe, BYD e6, Bolloré Bluecar, BMW ActiveE and RAV4 EV.
Extra-High	$E \geq 45\text{kWh}$	Tesla Model S.

Figure 2.1 General structure of an EV car

EVs use various types of batteries which are classified into three categories based on their characteristics, namely Lead-acid batteries, Nickel-metal hydride batteries and Lithium-ion based batteries.

The characteristics of the three battery types are compared in Table 2-2 and the typical charging curves are shown in Figure 2.2. The charging curves are based on the assumption that same charging rate is used. Charging rate of battery 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.

Table 2-2 Characteristics of different batteries used in EVs

Characteristics	Lead-acid[53]	Nickel-metal Hydride[54]	Lithium-ion[55]
Specific energy	25-40Wh/kg	60-120Wh/kg	100-265Wh/kg
Specific power	100-500W/kg	250-1000W/kg	250-340W/kg
Charge/discharge efficiency	50%–92%	66%	80–90%
Energy/consumer-price	7-18Wh/US\$	2.75Wh/US\$	2.5Wh/US\$
Self-discharge rate	3–20%/month	30%/month	15% /month
Cycle durability	500-800	500-1,000	400-1,200

Figure 2.2 Typical charging curves

Both Nickel-metal Hydride batteries and Lithium-ion batteries can be charged at a comparatively higher C-rate such as 1C-3C but it is not possible with Lead-acid batteries. Furthermore, both the Lead-acid batteries and Lithium-ion batteries have two distinct regions,

1. Constant current region where the charging power remains constant, and
2. Constant voltage region where the charging power changes with time.

With rapid advancements in the Lithium-ion battery technology, the use of other two types of batteries via Lead-acid and Nickel-metal hydride batteries are fading away. Almost all the new EV models launched in the recent years are using some variant of Lithium-ion batteries. This is due to the fact that the energy density and power density of the Lithium-ion batteries have increased drastically. Higher energy density and power density ensure sufficient energy for driving and facilitates faster refilling of the batteries. Such a feature will reduce the range anxiety of the EV users which is the one of the major hindrance for wide-spread adoption of EVs apart from the high initial cost.

2.2 Classification of EV charging

EV charging can be classified based on different criteria. The basic classification is driven by the rate of charging at which the EVs are charged. Based on the rate of charging, the EV charging is broadly classified into two types [56],

1. Fast charging, and
2. Slow charging.

Apart from the fast and slow charging classification, the EV charging is further classified into three levels, namely Level I, II and III based on the rate of charging. Table 2-3 shows the classification of EV charging stations based on their rated output power [52].

Table 2-3 Classification of EV charging stations based on their rated output power

Charger Type	Specifications
Level I	Voltage _{1-phase} = 120V, Current _{max} = 15A, Rated power $\leq 1.5\text{kW}$
Level II	Voltage _{1-phase} = 240V, Current _{max} $\leq 60\text{A}$, Rated power $\leq 14.4\text{kW}$
Level III	Rated power $> 14.4\text{kW}$

Level I and II charging stations belong to slow charging and level III belongs to fast charging. The definition of fast charging may vary from manufacturer to manufacturer. But the EVs which are commercially available in the market use 1C-3C as charging rate for fast charging and use CHAdeMO protocol for establishing the communication between the charger and EV [57].

The term 'C' defines the time taken for the EVs to charge to the rated capacity and is based on the rated power of the EV batteries. For example, for a 16kWh battery (corresponding to MiEV) the power required for 1C charging is 16kW and it takes approximately 1 hour to charge the battery to rated capacity. Similarly, the power required for 3C charging is 48kW and it takes about 20 minutes (1/3 of an hour) to charge the battery to rated capacity.

Generally, all fast chargers will be DC chargers and will be off-board chargers due to their considerably huge size [57]. The power rating of such type of chargers will be typically 20-50kW (peak) [57]. Fast charging is the most convenient of the available methods and decreases the range anxiety of commuters [57]. However, fast charging not only degrades the batteries faster [58] but also exhibits some disadvantages such as voltage flickers and voltage sags in the power system [59]. Furthermore, the convenience provided by fast charging is also accompanied by safety issues and high costs [57].

Slow charging can be further classified into three types [15]-[16], [18]-[19], [40] and [61],

1. Dump charging,
2. Delayed charging, and
3. Smart charging or coordinated charging.

If the rate of charging is $C/4$ or less, then it can be categorized as slow charging. Dump charging and delayed charging belong to the category of uncoordinated charging and smart charging belong to coordinated charging. Dump charging is the elementary (simple) charging strategy and does not require any control scheme. In this method, the EVs will start charging immediately after it is plugged in for charging. In delayed charging method, an intentional delay is provided so that the charging process does not coincide with peak load. Though in delayed charging method the EV charging does not

coincide with the peak load demand, the ramping cost is very high compared to smart charging.

Smart charging also referred as coordinated/regulated charging is the best charging strategy available in literature. As discussed in [40], the smart charging can be carried out in two different ways namely,

1. Smooth valley fill charging and
2. Flat valley fill charging

Figure 2.3 shows the classification of the EV charging based on different factors.

Figure 2.3 Classification of EV charging

Smooth valley filling has various advantages related to the power system operation as it provides reduction in ramping cost and smooth transition of generators. In smart charging method the charging of EVs is co-ordinated, and it ensures that the EV charging process does not coincide with peak load and optimal performance is obtained. Typical load curves of dump charging, delayed charging and smart charging are shown in Figure 2.4.

Figure 2.4 Typical load curves for dump, delayed and smart charging

2.3 Smart/Coordinated Charging

Coordinated charging of EVs, which also has other terminologies such as smart charging, regulated charging, and controlled charging is one of the most effective methods for integrating EVs into existing power system. In this method, the charging of EVs is carried out such that optimal performance can be obtained. There are various coordinated charging strategies available in literature [15], [40], [61]-[64]. Coordinated EV charging can be broadly classified into two types, i.e., time coordinated charging (TCC) and power coordinated charging (PCC).

The difference between TCC and PCC in terms of number of EVs being charged and the corresponding power consumed is illustrated in Table 2-4 using a typical scenario of six EVs connected for charging. It can be seen that in TCC, the number of EVs allowed to charge at a given time is controlled to ensure that the total EV load demand is within the total power available for EV charging. Whereas, in PCC, the power consumed by each EV is controlled to ensure that the total EV load demand is within the total power available for EV charging.

Table 2-4 Difference between TCC and PCC

Total power available for EV charging (kW)	TCC		PCC	
	Number of EVs charged	Average power consumed by each EV (kW)	Number of EVs charged	Average power consumed by each EV (kW)
9	3	3	6	1.5
12	4	3	6	2
15	5	3	6	2.5
18	6	3	6	3

Both the TCC and PCC methods aim to control the overall EV load demand to keep within the recommended limits in order to circumvent the impacts of EV charging on the power system operation. It can be observed from Figure 2.5 that in power controlled coordinated charging the power supplied to each and every EV is controlled at all instances such that the power limits are not violated. Whereas in case of time controlled coordinated charging the number of EVs charging at all the instances are controlled such that the power limits are not violated. The power limit is the constraint which is to be maintained for optimal performance. Time controlled coordinated charging has significant advantages as the converters used for charging the EVs mostly operate near their optimal power output. Since discontinuous charging will not affect the life and performance of the batteries [65] time coordinated charging can be used without any major performance degradation.

Figure 2.5 Typical load curves of PCC and TCC

However, time controlled coordinated charging requires an accurate load model for determining the charging demand of each EV and an effective scheduling algorithm for scheduling the EV charging with a set of constraints.

A real-time TCC is proposed in [19] for minimizing power losses and improving voltage profile during EV charging. The authors analyze the voltage deviation due to different scenarios of uncoordinated charging for different levels of EV penetration. The authors based on their analysis proposed a real-time TCC which utilizes tariff based priority and regulatory voltage limits as constraints. The advantage of smooth valley fill charging with the help of a TCC is demonstrated in [40]. The authors used different proportions of Level I and Level II chargers for their analysis. The intelligent EV charging strategy proposed aims to minimize the ramping cost of the power system. Methodologies for using priority based TCC are presented in [62] and [66] to achieve EV load leveling.

In [20], the aggregators control EV charging from 22:00 to 07:00 hours i.e., during off peak period. The amount of energy that needs to be purchased in each time interval is determined by the scheduling algorithm based on the price and EV charging demands. The EVs that are to be charged during the given time interval is determined by the dispatch algorithm. Novel solutions of using TCC for V2G application are demonstrated in [44] and [67] where different priority criteria are employed for scheduling of EV charging. In [44], the authors developed a dynamic scheduling algorithm for estimating the real-time V2G capacity that can be obtained from a group of EVs. The method has the significant advantage that the accuracy is not affected by time. In [67], the authors employed a dynamic programming algorithm to obtain the optimal charging control for each EV. The developed algorithm was applied for V2G frequency regulation services. Mathematical representation for the cost of battery charging and the revenue were also used for further investigations. In [62], the authors introduced a centralized EV charging method which can modify the total demand of EV charging without affecting the convenience of EV users. In [66], the objective is to maximize the overall profit by increasing the number of jobs completed before their deadlines and decreasing the penalty for uncompleted jobs. It included various threshold limits for scheduling the EVs.

A novel PCC method for mitigating the complications in the power system operation due to different levels of penetration of EV load is proposed in [15]. The authors analyzed the voltage regulation issues and power losses associated with uncoordinated charging

in residential grid. The proposed PCC minimizes the power losses and maximizes the main grid load factor. Furthermore, optimal charging profiles for the EVs are computed in the proposed method using stochastic programming. In [68], a PCC method which focuses on minimizing the variance in SOC is developed for achieving fair aggregation of EVs for V2G application. The authors used state-dependent allocation and water-filling approach both for up regulation as well as down regulation. The objective function of the optimization problem is to satisfy fairness criteria when the regulation service is provided by the EVs.

Research work in [41] proposed a PCC method that maximizes the total amount of energy which can be delivered to all EVs over a charging period while ensuring that network limits are not exceeded. In this work, a linear programming based approach is employed to determine the charging power which is optimal for each electric vehicle. The method was also tested on a section of residential distribution network. A novel PCC algorithm to intelligently allocate electrical energy to EVs connected to the grid based on priority criteria such as energy prices, battery capacity and charging time is proposed in [69]. Estimation of distribution algorithm (EDA) and a mathematical framework which aims at maximizing the average state-of-charge at the next time step were used by the authors. The proposed method was simulated for real-world parking deck scenarios using statistical analysis and transportation data. Another PCC method proposed in [64] uses EV charging profiles and energy prices as priority criteria for scheduling EV charging. The algorithm proposed uses the elasticity of EVs as loads for valley filling. Optimal charging profiles for all the EVs are obtained pertaining to the different conditions such as valley filling power, maximum charging rate and deadline.

2.5 EV charge Scheduling

Scheduling of EV charging forms the vital component in both types of coordinated EV charging methods. Though there are various scheduling algorithms available in literature [64], [68], [70]-[71], dynamic scheduling is inevitable to account the unpredictable load demand. The dynamic scheduling algorithms such as least laxity first (LLF) and earliest deadline first (EDF) are widely used for EV charge scheduling. In LLF, the priority values assigned to EVs depend the time required for completing the charging process and the total time available to complete the charging (departure time). EV which has the least difference between the time required for completing the charging process and the total

time available to complete the charging will get the highest priority. In EDF, the priority values assigned to EVs depend only on the total time available to complete the charging process. EV which is expected to depart first will get the highest priority.

In [70], maximizing the overall social welfare derived from factors such as total customer utility, cost of EV charging, and the penalty for not charging to the desired SOC at the time of departures. The authors used dynamic programming formulation for optimizing the charging process. In [71], the authors presented three heuristic causal scheduling policies namely EDF, LLF, and Receding Horizon Control [RHC]. The authors inferred from the simulation studies that EDF is optimal in the absence of power constraints. The authors also explored the performance of the scheduling policies based on required reserve energy and reserve capacity. The traditional and modified LLF and EDF used in [71] do not ensure proper operation. For example, 1) in case of LLF a vehicle with very high battery capacity and higher desired SOC will always have higher priority, and 2) in case of EDF even a vehicle with very high SOC will get very high priority if the departure time is very close. The factor related to the amount of energy supplied to the EV is not considered in any of the above methods. Appropriate choice of priority criteria is essential for robust performance of the EV scheduling algorithm. Furthermore, the customer's satisfaction achieved using traditional and modified robust dynamic scheduling algorithms [40]-[43] can be enhanced using proper combination of priority criteria. Generally, the priority criteria used for scheduling of EV charging can be categorized into 1) current SOC of EV battery, 2) slack time available for charging, and 3) time/energy already allotted for the EV.

A novel approach to minimize the difference between the individual SOC and the average SOC of each EV is discussed in [68]. The authors proposed a state-dependent utility scheme for allocating power to the EVs in proportion to their available battery SOC, a water filling algorithm for frequency regulation using V2G and variance minimization scheme to minimize the SOC variance with respect to the mean SOC of all EVs. However, it also results in similar disadvantages like LLF and EDF methods. Instead, combination of priority criteria can be used to obtain the priority value for EVs and the variance in the priority values can be minimized to overcome the disadvantages. For power controlled coordinated charging, dynamic programming and quadratic programming have been used in [15]. The output of the above algorithms is an optimal

charging curve considering few thousand historical load profiles. However, the algorithms do not consider the dynamic priority criteria and dynamic power allotment which are required for controlling the charging process where the load demand is highly unpredictable.

2.4 Impacts of EV Charging on Power System

Singapore's transportation system is a high efficient system in terms of energy required/head/km travelled. This is due to the fact that majority of the people in Singapore use public transportation system [72]. However in Singapore, personal vehicles out number other vehicles by a high margin (65-70%) [14]. Personal vehicles are the least efficient member of Singapore's transportation system in terms of energy required/head/km travelled. Converting the internal combustion engine personal vehicles into EVs will increase the efficiency of personal vehicles and hence the efficiency of overall transportation system. The most important disadvantage of EVs, i.e. lack of range is not a factor due to compact travel distances in Singapore.

The energy requirement of EV is compared with the average residential energy consumption in Singapore [2], [13], [50] in Table 2-5.

Taking into account the percentage of residents who own a car [14] in Singapore, the energy demand will become around 8% rather than 71.8 %, however can vary based on the actual number of EVs. Majority of EV charging happens overnight, and the energy has to be supplied during 1/4th to 1/3rd of the total time, i.e., in approximately 6-8 hours, so the total load due to EVs will be increased by 24-32% approximately from the current value. Any increase in load will increase the voltage regulation, power losses and THD, but it should be ensured that these factors are minimized to the possible limits.

Table 2-5 Energy requirement of a typical EV

Average energy required/km in kWh	0.2006
Average km/day (for Singapore)	55
Average energy required/day in kWh	11.00
Increase in average residential energy consumption (in %) with use of EV (average residential energy consumption =15.33kWh)	71.8

There are various obstacles for the deployment of EVs. One such is the impact of refueling EVs on existing power distribution network. The impacts which should be given primary importance are

1. Impacts on voltage profile of the distribution system,
2. Impacts on power demand and power losses,
3. Impacts on THD, and
4. Impacts on life of power system equipment.

2.4.1 Impacts on Voltage Profile of Distribution System

In [28], the authors have analyzed the voltage profile and voltage limit violation probability for two cases namely 25% and 50% of EV penetration using Monte-carlo simulations. The above simulations clearly showed that increase in penetration will result in increase of voltage limit violation probability. Furthermore, the heavily loaded feeders are affected more compared to the feeders with light and normal load. When the EV penetration is 25%, the decrease voltages is reasonable and within limits. However, for 50% penetration of EVs, the voltages dropped to considerably low values (below 0.93 p.u) in almost 50% of the buses. Also in more than 25% of the network buses, the voltages with higher degree of EV penetration violate the limit of 0.90 p.u.

In [15], the maximum voltage deviation for both coordinated and uncoordinated charging was analyzed for different levels of EV penetration using IEEE 34-node test feeder. It is observed from the simulation results that in case of uncoordinated charging the voltage deviations are approximately 10% particularly during evening peak periods when a penetration level of 30% is considered. However, the mandatory EN50160 standard [73] allows maximum voltage deviations of 10% in low voltage grids, for 95% of the time. The authors proposed deterministic and stochastic methods for determining the charging profile of EVs to reduce the impact of EV charging on voltage regulation. The authors demonstrated that the voltage deviations are below 10% following EN50160 standard even with the maximum penetration degree of 30% if coordinated charging is used.

Similarly in [18], the authors analyzed the voltage deviation beyond the desired limit for both coordinated and uncoordinated charging using 19-bus system. Simulation results were presented for three charging periods 17:00 - 08:00 hours, 17:00 - 24:00 hours and

also 17:00 – 19:00 hours which corresponds to the peak load period. Both the charging strategies via uncoordinated charging and uniform distribution charging over the available charging period are considered. Furthermore, three levels of penetration: 30%, 60% and 100% are considered. The results show that coordinated charging improves the voltage regulation from an unacceptable voltage level of 0.75pu at the worst bus to about 0.83p.u for a penetration level of 100%, i.e., worst case scenario. The voltage regulation of distribution transformers in a 1200 node smart grid distribution system was analyzed in [22] for different levels of EV penetration. The authors deduce that the transformers are able to maintain the voltages both on primary and secondary nodes within regulatory limits and the levels of EV penetrations do not have any significant impact. However, this is not consistent at nodes within low voltage residential networks especially the voltage deviations at radially distant locations showed major deviations in voltages.

Voltage deviation from rated voltage for different charging rates was analyzed in [59] and [74]. In [59], the analysis shows that the voltage deviations are not affected by the rate of charging with low level of EV penetration (20%). However, with 80% of EV penetration the voltage deviations are drastically affected by the rate of charging. The voltage deviation of quick charging is at least 200% of normal charging for all time zones. According to [74] coordinated charging improves the voltage profile for most of the cases and increase in fast charging will result in reduced voltage. An algorithm for real-time coordination of EV charging was proposed in [19] to minimize the impact of EV charging on voltage profile. A 449-node smart grid distribution system topology consisting of the IEEE 31 node 23 kV system with several 415 V residential feeders was used for the analysis. The impact of the algorithm for various levels of EV penetration was analyzed. The real-time coordination algorithm was able to reduce the voltage deviations for all the levels of EV penetration. All the above analyses clearly indicate that higher penetration of EVs will result in higher impact on voltage profile and coordinated charging can significantly reduce the impact EV penetration on voltage profile.

2.4.2 Impacts on Power Demand and Power Losses

The authors of [28] also analyzed the power demand and energy losses for two cases namely 25% and 50% of EV penetration using Monte-carlo simulations. It is observed

that the power demand in the peak hour increases by 41% and 109% for 25% penetration and 50% penetration respectively. There is an increase in daily energy demand also as expected. The daily energy losses increase by 58% and 140% for 25% penetration and 50% penetration respectively. In [75], the total load demand for different types of charging strategies namely smart and dump charging was analyzed and net CO₂ emissions were compared. In [15], ratio of power losses to total power was compared for different penetration levels and for both coordinated and uncoordinated charging. It is observed that the ratio was higher with uncoordinated charging compared to coordinated charging which indicates that uncoordinated charging results in higher power losses. Similarly in [18], the authors analyzed the total system losses for both coordinated and uncoordinated charging using 19-bus system. It is observed that the total system losses can be as high as 500% of the original value with uncoordinated charging during peak load. However with coordinated charging the EV loads are uniformly distributed and hence results in lower losses.

Distribution transformer losses in a 1200-node smart grid distribution system was analyzed in [22] for different levels of EV penetration. It is observed that EV charging has a significant impact on losses of low voltage residential transformer. For EV penetration levels between 2 to 40%, the transformer losses can increase up to 300% in which winding copper losses accounts for the major proportion. The transformer overloading as a result of high penetration of EVs (e.g., over 30% penetration) in peak time has an impact on service lifetime also. Power losses for different charging rates were analyzed in [59] and [74]. According to [59] the ratio of maximum power losses to total power increases with the increase in rate of charging as well as penetration levels. The results in [74] also deduce that the power losses increase with the increase in rate of charging as well as penetration levels. However, with coordinated charging the power losses are considerably lower.

An algorithm for real-time coordination of EV charging was proposed in [19] to minimize power losses. Furthermore, the change in the load demand due to the penetration of EVs and the impact of various charging strategies were discussed in [40], [61]-[62], [76]-[80]. In [76], a coordinated dispatch model of EV charging and wind power was presented. In [77], an EV charging strategy based on time-of-use electricity pricing market for peak load management. In [78], an analysis was performed for a power

grid demonstrating the impacts of coordination of charging. The factors such as charging time, charging patterns and penetration levels of EVs are considered. In [79], the impact of electric vehicle charging on residential low-voltage networks based on real life data driving patterns as well as large number of electricity networks was presented. In [80], the effects of EV battery charging were studied using a 3phase low-voltage residential distribution network model. Distributed Generation (DG) is also considered in the model used. The results of the above research works show that the system losses increase with the penetration level of EVs and can be minimized with different types of coordinated charging strategies. In [40], the power losses and ramping cost for different types of valley fill charging (coordinated charging) were presented in detail. All the above analyses clearly indicate that higher penetration of EVs will result in higher power/energy losses and coordinated charging can significantly reduce the overall system losses.

2.4.3 Impacts on Total Harmonic Distortion (THD)

As the EV charging involves the conversion of power through power electronic devices, it will not only result in increased voltage fluctuations but also higher harmonic distortions. The analysis in [81] provided an overview of the THD in voltage and current. The above analysis also compares the difference in THD while using active filters and while not using active filters. According to [81], voltage THD and current THD in the phase currents decreases significantly with active filters. The authors in [82] presented a statistical method for predicting the harmonic voltage level on distribution system due to the penetration of EVs. The authors determined the penetration levels possible with allowed THD limits. In [16], the authors analyzed the effect of THD on the distribution system particularly distribution transformers. The authors analyzed the impact of THD due to EV charging on different power system equipment such as transformers, cables, circuit breakers and fuses, etc.

In [83], the authors proposed using optimal dispatch prior to installation of passive or active filters. According to the simulation results for low penetration of EVs, optimal dispatching is sufficient to overcome the THD issues but in case of moderate penetration rescheduling might be required. However, in case of high penetration of EVs passive filter installation is mandatory. The authors of [18] analyzed the THD for both coordinated and uncoordinated charging using a 19-bus system. Simulation results are

presented for three charging periods 17:00 - 20:00 hours, 17:00 - 24:00 hours and during the peak load 17:00 - 19:00 hours. Both the charging strategies via uncoordinated charging and uniform distribution charging over the available charging periods are considered. Furthermore, three levels of penetration: 30%, 60% and 100% are considered. It is observed that uncoordinated charging results in THD voltage levels above the recommended limits of the IEEE-519 standard. The study clearly indicates that coordinated charging reduces the THD drastically compared to uncoordinated charging.

2.4.4 Impacts on Life of Power System Equipment

EV charging has serious impact on the life of transformers and cables [16]. The life of both transformers and cables depends on the hot-spot temperature. EV charging results in more heating due to the additional fundamental current as well as the heat generated by the losses due to THD. The consequence is higher hot-spot temperature and hence reduction in transformer life. The increased losses as a result of highly distorted currents coupled with harmonics will reduce the conductor life expectancy. The authors in [16] also deduced that the THD will affect the operation of circuit breakers and fuses. In [60], the impact of EV charging on the life of distribution transformer life was analyzed using an EV load model based on vehicle mass model. The authors used a case where six EVs were integrated to a 25 kVA transformer and Monte Carlo simulation was used to predict the EV load demand. The analysis was carried out for different levels of EV penetration in terms of loss of life for the transformer. The results indicated that high penetration and uncoordinated charging have significant detrimental effect on the transformers' life.

The authors in [60] investigated two potential approaches for charging the EVs. It is observed that intelligent coordination for charging the EVs helps in mitigating the transformer loss of life issues associated with EV charging. The analysis clearly illustrates that coordinated charging has less impact on transformer life compared to uncoordinated charging. In [84], the authors presented a method to determine the EV charging demand under both uncoordinated and coordinated charging. The authors evaluated the impact of EV charging on the distribution transformer hotspot temperature and loss of life. It is observed that uncoordinated charging increases the peak demand which further results in increased loss of life for transformers whereas coordinated charging of EVs will assist in mitigating such issues. The impact on transformer life can be extended to cables also [85]. There are various simulation models and standards

available in literature for calculating the hot-spot temperature and the loss of life of transformer which can be further used for various analyses [86]. All the above analyses clearly indicate that higher penetration of EVs will result in higher loss of life for distribution transformers and cables. The operation of other power system equipment is also affected. Hence coordinated charging is required to optimally utilize the power system equipment.

2.4.5 Suitability of the Charging Strategies in Singapore's Context

The authors of [74] have analyzed the impact of fast chargers of rating 11.4kW on voltage regulation and power losses. The analysis shows that fast chargers have much higher impact of voltage regulation and power losses. Since fast chargers use very high pulse power, the THD component will also be very high. This implies that the real chargers which have much higher power rating will have effects much worse than this case. However this analysis is performed for distribution transformers of capacity 100kVA. In case of Singapore where the distribution transformers are of much higher capacity typically 1-2.5MVA [35], it will be feasible to install 1-2 fast charging stations in each distribution transformer without causing major impact. Proper planning is required to avoid the disadvantages of fast charging on power distribution systems. For example usage of the charging station should be avoided during the peak hours so that the voltage regulation, power losses, THD and loss of life of transformers and cables can be kept under the prescribed limits. Moreover the fast charging stations installed with distribution transformers of commercial buildings can be used during off-peak period between 22:30 hours to next day 06:30 hours. This will increase the utilization of the building resources. But fast charging will be seldom used in Singapore as range extension is not required due limited available land area. So the number of fast charging points can be very less and can be intended only for emergency cases.

The biggest problem with dump charging method is that the starting of EV charging coincides with the peak demand. Due to which the effects on voltage regulation, power losses, THD and life of transformers and cables will very high if the total load is greater than the rated capacity. Dump charging can be used only during initial period of EV deployment until the point when addition of EV load does not make the total load to be more than the rated capacity. Dump charging cannot be used to charge EVs when they

are parked in work place also, as it would cause serious loading issues during peak loading period.

In literature delayed charging is also categorized in uncoordinated charging hence the results discussed for dump charging holds for this case also. However, these results do not hold for Singapore as the capacity of the distribution transformers are much higher (1-2.5MVA). Proper selection of delay time can ensure a good percentage of EV deployment without any major impact. Moreover, since the off-peak hours are used for charging the EVs, impacts on the voltage regulation, power losses, THD and life of transformers and cables will be within the limits. This method can resemble the valley filling strategies used in [40].

Advantages of delayed charging in Singapore context include:

1. Require simple control scheme and components,
2. Better performance compared to dump charging, and
3. More number of vehicles can be charged with less impact compared to dump charging.

However, in this method we do not have complete control over the charging of electric vehicles and has a poor performance during unexpected emergency loading condition. Delayed charging technique can be very useful during initial deployment of EVs when the number of vehicles is not very high. Delayed charging can be used either as replacement for dump charging or can be considered right from initial deployment as it gives better performance. It is clear from the above analysis that coordinated charging is the best charging strategy available in literature as it gives the best performance in terms of impacts on voltage regulation, power losses, THD and life of transformers and cables. In literature there are two important schemes for smart charging namely flat valley filling, smooth valley filling [40], the above analysis demonstrates that smooth valley filling is more efficient than flat valley filling.

2.5 Load Modeling for Determining EV Charging Demand

The charging demand of an EV (Renault Kangoo) owned by Singtel is shown in Figure 2.6. The charging demand was collected using smart meters installed at the upstream of

Figure 2.6 Charging curves of Renault Kangoo EV on different days

Bosch Level II charger at NTU. All the analyses on the impacts of EV charging on power system use some kind of load modeling for determining the charging demand of EVs. In most of the cases the power rating of the charging equipment was considered as the load demand and few cases the energy demand was used for modeling the load demand. However, it can be observed from Figure 2.6 that the charging demand is not constant on every day. Hence considering the initial SOC is important for obtaining accurate load model. Besides [17], no other research in the literature considers the initial SOC and type of battery for determining the charging profiles/demand of EVs. The load modeling should consider factors such as initial SOC, final SOC and type of battery. Considering the type of battery is very important because the batteries with constant voltage region

Figure 2.7 Functional diagram of DDM [87]

as shown in Figure 2.2 will have different type of power requirement in constant voltage region. The impact of aging of the battery and other components of the charging equipment also plays a key role [63] hence both should be taken into account while modeling the EV charging demand. If the effect of aging is not considered, then the error in determining the load demand increases with age of the battery and other equipment. With an effective scheduling algorithm, such a load model will ensure that the EVs are charged to the required final SOC always.

Data driven modeling (DDM) which is commonly used in hydrology and various forecasting applications is a good candidate for determining the charging demand of EVs. In DDM the data characterizing the load and machine learning are used instead of actual physical process. It has better performance than conventional empirical modeling [87]. It can be applied to various fields such as solving numerical prediction problems, to reconstructing highly non-linear systems, data classification and grouping, and to develop rule-based systems. There are various methods using which data driven

Figure 2.8 A typical structure of ANN

modeling can be developed, but artificial neural networks (ANNs) are considered in this research due to their simplicity. Functional diagram of DDM is shown in Figure 2.7 [87].

2.5.1 Artificial Neural Networks (ANNs)

ANNs are a network which considers the nodes as artificial neurons, and are a modeling inspired by natural neurons of human brain [88]. In ANNs the inputs are multiplied with weights by mathematical function for activating a neuron. A typical structure of ANN is shown in Figure 2.8. The predicted outputs are compared with the desired outputs and the weights are adjusted to meet the requirements. The process of adjusting the weights is called training or learning. One such training algorithm is back propagation [45] and is mainly used in feed-forward networks. In back propagation method, the training starts with random weights and the weights are adjusted until the error in predicted values is minimized to desired level or range.

2.5.2 Data-Driven Simulations

As onset of smart grid will provide a large data which is earlier unavailable, the data-driven simulations are an attractive option for determining and controlling the various aspects of the EV integration. The use of data-driven simulations is an effective solution for evaluation of EV charging strategies. Furthermore, it is feasible to accurately evaluate the overall performance. Data-driven simulations offer a wide variety of advantages. Updating the model parameters to account for the changes due to ageing is one of the major advantages. Furthermore, scaling up the system to account for new additions is relatively simple. The effectiveness of data-driven simulations and controller design using data-driven modeling has been studied by many authors [36]-[39].

In [36], the authors presented a multidisciplinary problem solving environment with the architecture of a data-driven environment for multi-physics applications. The environment will enable the automated identification as well as efficient prediction of the behavioral response of multi-physics continuous interacting systems. The authors in [37] surveyed the inherent problems and challenges associated with model based control theory. A review on the important issues and design of data-driven control methods were presented. A dynamic data-driven application simulation was developed by authors of [38]. The method proposed by the authors offers solutions for interesting computational and mathematically unsolved problems. In [39], a novel data-driven control approach and model-free adaptive control was presented. A new dynamic linearization technique

for a class of discrete-time single-input and single-output nonlinear systems is used for developing the approach. The attractive feature of the above approach is that the controller design depends only on the measurement data from input and the output sides of the controlled plant. The architecture used for data driven simulation is shown in Figure 2.9. The physical system consists of power supply from the grid, EV chargers and the actual EVs in a smart grid network. The cyber system collects and stores data like load demand of the smart grid network without EVs, charging profiles of EVs, arrival, departure and per day travel distance pattern of each EV, etc.

Figure 2.9 Model for data-driven simulations

2.6 Vehicle to Grid

The V2G is a concept in which energy from EV is pumped to grid. It has various other terminologies such as Vehicle to Home (V2H), Vehicle to Building (V2B) etc. V2G can be used for many applications such as to supply additional energy during periods of maximum demand or high electricity price. The V2G concept also enables the utilization of EV batteries as storage for leveling the intermittency of RESs. For utilizing EV batteries as SES, V2G capacity has to be estimated in real-time for efficient and optimum control of the V2G operation.

In [89], the authors described a mathematical model for estimating the V2G power capacity of a parking lot. The queuing theory problem is used for formulating the models. The paper not only presents the modeling of V2G power demand but also supply along with evaluation for electricity market potentials. In [90], the authors developed equations for calculating the V2G capacity of three types of EVs. The equations are used for evaluating the revenue and costs while using EVs for peak power, spinning reserves, and regulation services. In [67] an aggregator utilizing the distributed power of EVs to provide V2G frequency regulation services was presented. Mathematical representation for the cost arising from the battery charging and the revenue obtained from the regulation services are presented and investigated.

In [91], based on the necessity for estimating the amount of power that can be delivered from EVs to grid for practical V2G services, achievable power capacity (APC) is estimated using probabilistic method. The probability distribution of the APC is used to calculate the contracted power capacity (CPC). The CPC is defined as the power capacity that V2G aggregators are contracted to provide to grid operators. The authors of [92] presented an analysis for utilization cost of using EVs as energy storage in power grids. The reduction in battery cycle life as a result of frequent charging and discharging activities is studied. In [68], application of V2G aggregators for frequency regulation based on fair use of EV energy storage capacity is studied. The optimization of aggregator profit is carried out using different methods, namely state-dependent allocation and the water-filling approach. It is ensured that the final SOC of the EVs are reached while full filling the fairness criteria.

In [93], a detailed review of literature on the current status and implementation impact of V2G technologies on distributed systems, requirements, benefits, and challenges was presented along with the strategies for V2G interfaces of both individual EVs and fleets. In [25], a V2G algorithm for optimizing energy and ancillary services scheduling was developed. Load regulation and spinning reserves are the ancillary services considered in the research work. Either the utility or a third party which functions as the aggregator can employ the algorithm. The authors in [94] presented a model of aggregated EV based storage for using in long-term dynamic power system simulations. An analysis on power system regulation services for high and low wind production in the Western Danish power system was also presented.

The V2G estimation methods available in the literature mainly focus on determining the achievable power capacity for a group of EVs [67], [91]. Apart from the capacity estimation, other methods were proposed for aggregating EVs and supplying V2G power to the grid [25], [89]-[94]. The aggregation process is also governed by the amount of power and energy that the EVs can supply during any given interval.

V2G can be categorized into the following types:

1. Heavy utilization: For example, the EV batteries can be used as distributed storage to store off-peak power and use it for peak shaving.
2. Medium utilization: For example, the EV batteries can be used as storage for tackling the intermittency of RES.
3. Light utilization: For example, the EV batteries can be used for auxiliary services like frequency regulation, reserves (similar to spinning reserves) and emergency backup for black out conditions, etc.

However, V2G requires using up a fraction of battery life [90], [95]. The EV users may be reluctant to enter into an agreement with building operators unless there are considerable monetary or convenience benefits. Hence a proper demonstration of the advantages is necessary with proper policies. The trend for acceptance among the users will be from application 3 to 1. Because in application 1 the EV battery will be used every day and in application 3 EV battery will be used only under transient and emergency conditions.

In Singapore, the plan of the government is to promote the integration of solar photovoltaics (PVs) on rooftops of high-rise Housing Development Board (HDB) residential buildings [5]. In the last few years, there has been a prolific growth in the integration of solar PVs into the distribution network in Singapore [6], [7]. Hence, medium utilization i.e., EVs being used as storage for handling the intermittency in solar PVs will be more prevalent. Case studies for such applications are discussed in Chapter 4.

2.7 Demand Response

The rapid urbanization with increasing population and demand for a better quality of living has led to a greater usage of energy. Singapore, being a highly urbanized country, has approximately 17% of the total energy consumed in 2005 by buildings [7]. Instead of increasing the energy production from traditional carbon based sources to meet this growing demand, managing and controlling the energy utilized by buildings through demand response management (DRM) will ensure lower overall demand and consumption energy.

Highly urbanized cities around the world such as Singapore are looking at mass deployment of EVs to achieve a cleaner and greener mobility. However, large-scale penetration of EVs will increase the load requirements of buildings. Furthermore, if the additional load due to EVs is not managed properly, it can easily result in the building's total load demand exceeding its demand limit imposed by the utility [47]. EVs are generally considered the lowest priority load that will be shed first before any other load shedding occurs. This is because temporary discontinuity of EV charging will not have significant impact on the EV owner satisfaction/comfort provided that the owner's required SOC at departure can be achieved. The EVs will be charged in groups as they will be charged at parking lots with charging stations installed and controlled by the building owner. Such a charging pattern is highly suitable for using EVs in DRM as flexible loads and offers wide range of load demand control.

In [96], investigation of different charging strategies and demand response management possibilities were explored for a car park. The arrival times and parking durations were obtained from the available data and statistical information. The charging of individual EVs is assumed controlled by the car park operator. With the above conditions the effects

of demand response management on the total charging cost of the system are analyzed. In [97], a demand response strategy was proposed to minimize the impact of charging EVs on a distribution circuit of a smart distribution network. Severity Indices are used for executing the demand response of EVs. In [98], a new model of demand response management for the future smart grid integrating EVs and renewable distributed generators was proposed. In [99], a demand response strategy to increase the potential for adding new load with minimal infrastructure investments was proposed. It also serves as a load shaping tool for improving the usage of distribution transformer. The authors take into account consumers' preferences, load priorities, and privacy.

In [100], two demand response programs were presented namely the trip reduce demand response and trip shifting demand response. The use of the above demand response models is activated every time when the energy price reaches a predefined value. In [101], the authors investigated dynamic demand response for intelligent EV charging. A detailed hybrid model was proposed to handle problems that cannot be properly handled by traditional tools alone. In [102], a distributed framework for demand response and user adaptation in smart grid networks was proposed. The authors use the concept of congestion pricing in internet traffic control and applied it to regulate user demand and hence balance network load. The authors of [103] demonstrated the applicability of a novel pool market mechanism for re-schedulable demands such as EVs which have flexible charging capability.

In Singapore, as EVs will be parked in groups, there is very high potential for using EVs in various demand response applications. Furthermore, group of EVs can be combined to create flexible load demand which can be used for overall load management in different types of high-rise buildings. Case studies for such applications are discussed in Chapter 4.

2.8 Summary

Increase in deployment of EVs will increase the load demand on the distribution system and coordination of EV charging is essential for mitigating the major complications. Smart/coordinated charging is an attractive solution and can be employed in different forms namely time coordinated charging and power coordinated charging. Data-driven

modeling and simulations are attractive options for determining the performance of the coordinated charging methods. Employing scheduling for determining and managing the auxiliary functions of EVs such as V2G and DRM has significant advantages. Extensive research has been conducted by various authors on these aspects of EV integration. However, few areas require further attention to increase the robustness of the methods proposed for deployment of EVs.

CHAPTER 3 PRIORITY BASED DYNAMIC EV CHARGE SCHEDULING

In this chapter, the model used for determining the load demand of EVs, the priority criteria considered for scheduling the EVs, two types of coordinated charging algorithm via Time Coordinated Charging (TCC) and Power Coordinated Charging (PCC), and the impact of different combination of priority criteria on the chargeability of EVs and fairness in time/energy allotted to the EVs are presented and discussed. The concepts presented in this chapter are based on author's publications [44]-[46].

3.1 EV Charging Profile Prediction

As discussed in Chapter 2, the charging profile of an EV varies based on various parameters such as initial SOC, final desired SOC, battery type and charging/discharging cycles completed. Predicting the charging profiles of EVs will enable various energy management applications such as maximum demand prediction, EV charge scheduling and demand response management. These applications are essential to improve the energy efficiency and optimize the charging efficiency. The predicted EV charging profiles and the forecasted building load profile can be utilized for various functions such as determining the V2G capacity, demand response management and performing load/source scheduling.

As discussed in Chapter 2, besides [17] no other research in the literature considers the initial SOC as well as type of battery for forecasting the charging profiles of EVs. This is particularly important as the EVs are not required to charge from 20% of SOC to 100% of SOC each time they are plugged for charging [29] which can also be observed in Figure 2.6 of Chapter 2. This is because the initial SOC at arrival and the user's desired SOC at departure will vary according to the owner's preference and the daily travel distance of the EV. Therefore, the actual charging profile of an EV can be determined more accurately by considering the initial SOC at arrival, the desired SOC at departure and the type of battery used. Furthermore, the aging process of the battery, which is determined based on the equivalent number of charging cycles undergone, will also have an impact on the forecasted charging profile [64]. Hence by considering historical charging profiles of the particular EV will significantly improve the accuracy of the predicted charging profile. The EV charging is a nonlinear process and changes regularly

due to the chemical composition of the battery.

The procedure for generating historical charging profiles of a particular EV is given below.

$$P_{actual}^n = \left(\frac{P_{cc1}}{\eta} \right) - \left(0.1 * \frac{P_{cc1}}{\eta} \right) + (W * 0.1) \quad (3.1)$$

where, P_{actual}^n is the actual power required, P_{cc1} is the power demand during constant current region, W is a pseudo-random integer variable uniformly distributed over an interval $[0, 10]$, η is the efficiency of the power converters [50], [104] and n is any instant in the charging interval. The efficiency of the power converters is assumed to be 0.85. The minimum possible SOC is taken as 10% and the power demand from 10% to 80% of SOC is generated for each minute. Then, the increment in the SOC is computed by

$$SOC_{new} = SOC_{old} + \left[\frac{P_{actual}^n}{P_{1c}} * 100 \right] \quad (3.2)$$

where, SOC_{new} is the incremented SOC due to the power supplied during the previous one minute duration, SOC_{old} is the previous minute SOC, P_{1c} is the power required for charging the battery at the rate of 1C (~100% SOC in 1 hour). Subsequently, the power demand for 80% to 100% of SOC is generated by calculating the slope of power P_{slope} decrement using time required for constant voltage region. The calculated slope is subtracted from P_{actual}^n after every minute until 100% SOC is reached.

$$P_{actual}^n = P_{actual}^{n-1} - P_{slope} \quad (3.3)$$

Similar procedure is followed for different levels of aging, for example, from 0 to 500 cycles, P_{cc1} is decreased by 5% for every 50 cycles to account the degradation of the battery health [63]. Using the historical charging profile, the current charging profile is predicted using an artificial neural network.

3.1.1 Artificial Neural Network Model

The proposed artificial neural network (ANN) model is highly suitable for predicting the charging profiles of EVs as it is adaptive to changes due to its ability to learn. The proposed ANN forecasting model is designed based on a three-layer (input layer, hidden layer and output layer) feed-forward with back propagation as a training algorithm. The input of neurons to the ANN implementing the back-propagation algorithm is the sum of the weighted inputs which is then combined with a constant bias. The weights are updated iteratively and the error is reduced indicating that the neural network is learning. The neural network consists of two inputs in the input layer, one output in the output layer and four hidden neurons in the hidden layer. A tangent sigmoid is used as the activation function for all the neurons in the neural network. The proposed ANN model for prediction of charging profile is shown in Figure 3.1.

Data pre-processing is required as missing and irregular charging profile data items are natural. For example, a vehicle may follow particular traveling pattern and hence may always have charging profile within a specific range of SOC. In such cases data for the charging profile of remaining range of SOC (above and below) will be unavailable. For such cases either the data of other similar vehicles or data from battery manufacturer can be used. Thus, data pre-processing is necessary to fix data problems. The typical curve fitting method is used to pre-process the historical data available. Data spikes, missing data and redundant data items are identified and replaced with typical curve values.

The charging demand varies based on the SOC of the battery. The choice of number of neurons (for each layer) will depend on the accuracy requirements and allowed complexity. In the proposed method, the number of networks is selected based on number of minutes required for charging the EV from 10% to 100% and the number of input neurons in each network is selected based on the number of previous charging profiles used. The input of neurons in the hidden layer is a weighted inputs sum of X_i . X_i is the power consumed by the EV at a given instant and i represents the previous charging profile's id. The weighted sum is then combined with a constant bias and is passed through a tangent sigmoid transfer function to obtain b_f which is given by

$$b_f = f\left(\sum_{i=1}^n V_{i,j} X_i + \theta_j\right) \quad (3.4)$$

Figure 3.1 ANN model used for predicting the charging profile of EVs

The obtained b_f is used as the input for the output layer, combining it with a constant bias and passing it through a linear transfer function gives

$$c_f = f\left(\sum_{i=1}^n W_{i,k} b_i + \gamma_j\right) \quad (3.5)$$

C_f is the output which is compared with target output (the latest charging profile). The training is continued and the weights are adjusted until the desired training goal is reached. The weights are initialized with random values to begin with. $V_{i,j}$ is the weight between input and hidden layer, $W_{i,k}$ is the weight between hidden layer and output layer, θ_j and γ_j are the constant bias used with $V_{i,j}$ and $W_{i,j}$ respectively.

In the proposed method, incremental load method is used. In order to train with incremental load method, the training data is first converted to relative incremental values by the following equation:

$$\delta_{t+m} = \frac{L_{t+m} - L_t}{L_t} \quad (3.6)$$

where δ_{t+m} is the relative incremental of the actual load at time $(t+m)$, L_{t+m} is the actual load at time $(t+m)$, L_t is the actual load at time t and m is the lead time of the forecast. In this project, m is taken as 1 minute. The forecast values are obtained from the forecasted relative incremental load by

$$\hat{L}_{t+m} = L_t * (1 + \hat{\delta}_{t+m}) \quad (3.7)$$

where $\hat{\delta}_{t+m}$ is the forecasted relative incremental of the actual power, and $\hat{L}_{t+m}$ is the forecasted power at time $(t+m)$.

The mean absolute percentage error (MAPE) of the forecasted load is then computed by

$$MAPE = \frac{1}{n} \sum_i \frac{abs[P_F(i) - P_A(i)]}{P_A(i)} * 100\% \quad (3.8)$$

where n is the total number of samples; P_F is the forecasted power, and P_A is the actual power.

The result of the ANN model for charging profile prediction is shown in Figure 3.2. The charging profile is predicted for the SOC range of 10 - 100%. The MAPE obtained is 4.47%. It can be seen that the predicted charging profile is very close to the actual target and thus can be used for various building energy management applications such as maximum demand prediction, electric vehicle charge scheduling and demand response management. The main advantage of the proposed method is that the accuracy of the results is not affected by the age of the battery.

Figure 3.2 Result of prediction from ANN

3.1.2 EV Load Demand

Utilizing the predicted charging profile, the unscheduled total demand of EVs can be obtained as

$$p_j^{uEV,i} = \begin{cases} 0, & 1 \leq j < (m_i - k_i - 1) \text{ \& } j \geq m_i \\ p_l^{EV,i}, & (m_i - k_i - 1) \leq j \leq (m_i - 1) \end{cases} \quad (3.9)$$

where m_i is the departure interval of i^{th} EV, k_i is the total number of intervals required for charging the i^{th} EV and l is given by

$$l = j - (m_i - k_i - 2) \quad (3.10)$$

In order to clearly illustrate the unscheduled total demand of EVs as given by (3.9), a typical example with $m_i = 8$ and $k_i = 3$ is shown in Figure 3.3 where each interval corresponds to 30 minutes. Based on (3.10), l is less than or equal to zero up to $j=3$ and greater than 3 for $j > 7$. This means that $p_l^{EV,i}$ is '0' for the 2 intervals (i.e., intervals 2 and 3) and when l becomes '1' at $j=4$ and '4' at $j=7$, then $p_l^{EV,i}$ will have a positive value. Hence, based on (3.9), $p_j^{uEV,i}$ is '0' for $1 \leq j < 4$ and $j \geq 8$, and $p_j^{uEV,i}$ is equal to $p_l^{EV,i}$ for $4 \leq j \leq 7$. Similarly, this method can be used to obtain the load demand of each EV.

The maximum value of m_i gives the interval in which the last EV departs and is represented as

$$m_{max} = \sigma_{max}(m_i) \quad (3.11)$$

Figure 3.3 Unscheduled load demand of an EV

The departure interval selection process is denoted by σ and the propositional formula to select the departure interval of the last EV to depart is denoted by subscript ‘ max ’.

3.2 Priority Criteria

Generally, the priority criteria used for scheduling of EV charging are 1) current SOC of EV battery, 2) slack time available for charging, and 3) time/energy already allotted for the EV based on the methods available in literature (discussed in Chapter 2). Appropriate choice of priority criteria is essential for robust performance of the EV scheduling algorithm. Furthermore, the customer’s satisfaction achieved using traditional and modified robust dynamic scheduling algorithms [40]-[43] can be enhanced using proper combination of priority criteria.

The three priority criteria based on the above parameters are listed below:

1. α_i^1 represents the priority criterion based on the SOC of EV battery as given by (3.12);
2. α_i^2 represents the priority criterion based on the slack time available for charging as given by (3.13);
3. α_i^3 represents the priority criterion based on the time/energy already allotted for the EV as given by (3.14).

$$\alpha_i^1 = 1 - \left(\frac{SOC_i}{100} \right) \quad (3.12)$$

$$\alpha_i^2 = 1 - \left(\frac{N_{dep,i} - N_{req,i}}{N_{total,i}} \right) \quad (3.13)$$

$$\alpha_i^3 = 1 - \left(\frac{E_{sup,i}}{E_{total,i}} \right) \quad or \quad 1 - \left(\frac{N_{com,i}}{N_{total,i}} \right) \quad (3.14)$$

where i is the EV number. α_i^1 is the priority parameter which accounts for the current SOC of the i^{th} EV. SOC_i is the battery SOC in percentage (%) of the i^{th} EV. The customer's satisfaction will be higher if the EV can be charged to the desired SOC before

departure. As expressed in (3.12), the priority value will decrease with increase of SOC, hence the EV with lower SOC will have higher priority value. This parameter is essential for achieving higher customer's satisfaction. α_i^2 is the priority parameter which accounts for the slack time available for charging the i^{th} EV. $N_{dep,i}$ is the number of half-hour time intervals from current time to departure time for the i^{th} EV. $N_{req,i}$ is the minimum number of half-hour time intervals required for charging the i^{th} EV up to the desired SOC. $N_{total,i}$ is the equivalent number of half-hour time intervals required for charging EV from initial to desired SOC. Slack time is the difference between the time available before departure and time required to complete charging. With higher the value of slack time, the feasibility of charging the EV to desired SOC is higher, thus the priority value will decrease with increase in slack time. This will enable the EV with lower the value of slack time to have higher priority for charging as expressed in (3.13). This parameter is required to ensure higher degree of fairness to the EV owners. α_i^3 is the priority parameter which accounts for the percentage of charging completed. $E_{sup,i}$ is the energy supplied to the i^{th} EV and $E_{total,i}$ is the energy required to charge the EV from the initial SOC to the desired SOC. In the case of TCC, $N_{com,i}$ is the equivalent number of half-hour time intervals used for charging the i^{th} EV. The percentage of charging intervals completed for the i^{th} EV represents the amount of resources already allocated for that particular EV. Therefore, the higher the $E_{sup,i}$ or $N_{com,i}$, the lower will be the priority for charging as indicated in (3.14). This parameter is required to balance the degree of fairness between the EVs having the same battery capacity.

3.3 Coordinated Charging

The dynamic scheduling algorithm proposed in this research uses a data-driven scheduling approach to overcome the disadvantages of existing scheduling methods while providing a robust algorithm compared to those available in literature. The load demand of the smart grid network consisting of m (450 in this case) number of residential units without EVs is represented as

$$p_j^{loaddemand} = \sum_{x=1}^m p_{x,j}^{resunit} \quad \forall j = 1, 2, 3, \dots, 48. \quad (3.15)$$

$$p_{x,j}^{res\ unit} = rand(\mu_{x,j}, \sigma_{x,j}^2, pdf_{x,j}) \quad (3.16)$$

where $\mu_{x,j}$, $\sigma_{x,j}^2$ and $pdf_{x,j}$ are the mean, variance and probability density function of respective units in a given interval. 'x' and 'j' represent the residential unit number and half-hour interval respectively. The load demand data is collected from the smart meters installed in few residential units of Nanyang Technological University (NTU) campus. Load demand data for a period of one year is used to determine the mean, variance and probability density function of the load demand. 450 units are considered for obtaining the base load without EVs and the number of units represents a typical group of Housing development Board (HDB) blocks in Singapore. The values obtained are then used for the stochastic simulations as given by (3.16). The power limit p^{limit} for ensuring that the EV load demand does not exceed a predetermined value can be obtained using the method discussed in [49]. The method proposed in [49] uses transformer's hotspot temperature and loss of life for determining the value for p^{limit} and is described in detail in Chapter 5.

Another method (used in this research) to obtain p^{limit} is to find the power limit required for smooth valley filling which is essential for optimal power system operation [40] and the average power required for having a smooth valley filling is obtained by

$$p^{limit} = \frac{\sum_{j=1}^{m_{max}} (p_j^{load\ demand} + p_j^{uEV})}{m_{max}} \quad (3.17)$$

where

$$p_j^{uEV} = \sum_{i=1}^n p_j^{uEV,i} \quad (3.18)$$

The contracted capacity or maximum power demand limit p_{CC} can also be used as the power limit. The electricity industry in Singapore is categorized into two sectors, contestable and non-contestable. In general, commercial buildings with an average monthly consumption that exceeds 10,000kWh qualify as contestable consumers. Contestable consumers can purchase electricity from an electricity retailer or from the wholesale market either directly as a market participant or indirectly through Singapore

Power (SP) Services. Electricity from wholesale market is charged at “spot price” which fluctuates every half an hour according to supply and demand while electricity from electricity retailers is charged according to a pre-negotiated supply package [105].

Consumers may choose not to apply for contestability and remain as non-contestable, but all consumers in Singapore will eventually become contestable when the retail electricity market is fully liberalized to promote the efficient supply of competitively priced electricity [106]. Non-contestable consumers are supplied with electricity by the public utility (in this case, SP Services Ltd.) at regulated tariff. The electricity tariff is revised every three months to reflect the actual cost of electricity and it is approved by Energy Market Authority (EMA) [105].

Commercial buildings are treated as non-contestable consumers and charged under High Tension Small (HTS) Supplies tariff category. The usage charge includes contracted capacity charge, un-contracted capacity charge, peak period charge, off-peak period charge and reactive power charge. The tariffs (applicable from April 2011 to June 2011) are shown in Table 3-1 [107]. Contracted capacity charge is a monthly charge payable for the supply capacity (in kW) requested at each metered intake supply point of a consumer and the charge is always payable irrespective of the maximum overall load demand measured. In addition, the consumer is not allowed to change the declared contracted capacity for a period of 5 years [107]. The purpose of contracted capacity charge is to encourage better load management, thus preventing uncontrolled growth of demand. In order to keep up with the growth in peak load, which usually only occurs a few times in a year, utilities need to build capital-intensive power plants and transmission lines. This consequently requires an increase in the tariff to recover the large capital expenditures. 10% to 20% of overall electricity costs in the United States are due to peak demand which translates to only 100 out of 8760 hours of the year [108]. Furthermore, the construction of new power plants leads to increase in greenhouse gas emissions since most plants still rely on traditional carbon based energy sources currently.

Un-contracted capacity charge is a monthly charge payable for the amount of maximum overall load demand (in kW) measured by the half-hour integration meter that exceeds the contracted capacity at that metered intake supply point [107]. Besides encouraging better load management, un-contracted capacity charge, which is of higher rate than

contracted capacity, discourages sudden surge in demand that might lead to blackout or disruption in service. Peak period charge is payable based on the energy (in kWh) supplied to an installation during the peak period, 07:00 to 23:00 hours, whereas the lower off-peak period charge is based on the energy supplied during the off-peak period, 23:00 to 07:00 hours [107]. Lower off-peak period charge encourages consumers to change their unfavorable energy usage patterns that have high peaks and low troughs to smoother ones to avoid under-utilization of cheap generation during off-peak period.

Reactive power charge is a charge payable for the installation's excess kVArh (reactive power) consumption, where the installation's kVArh consumption drawn from the network in that month is greater than 62% of its kWh (real power) consumption drawn from the network in the same month [107]. Reactive power charge is used to penalize energy users with low average power factor (pf). Low pf increases I²R and I²X losses in the transmission lines and hence reduces thermal capability which requires costly and larger diameter wires to be installed. Moreover, to deliver same amount of real power, utilities have to increase capacity requirements. Note that 62% threshold corresponds to an average pf of 0.85 lag.

Therefore, based on the various charges that are imposed to building owners, it is crucial for them to carefully consider the contracted capacity according to the expected maximum demand in order to minimize their annual electricity costs. However, in the event of excess consumption, the building owners have the choice of paying an extra charge (penalty) for the un-contracted capacity, or to introduce energy management system that enables the integration of distributed energy resources to shave a portion off the maximum power demand and to dynamically perform demand side management to reduce maximum demand.

Table 3-1 Utility charges for buildings

Usage charge	With effect from April 2011 (with 7% GST)
Contracted capacity charge	\$7.45/kW
Un-contracted capacity charge	\$11.17/kW
Peak period charge	\$0.2578/kWh
Off-peak period charge	\$0.1581/kWh
Reactive power charge	\$0.0063/kVARh

Therefore, it is crucial for building operators to carefully consider the contracted capacity according to the expected maximum demand in order to minimize their annual electricity costs. However, in the event of building's total load demand exceeding its contracted capacity, the building operators have the choice of paying a penalty charge for the uncontracted capacity. However, p^{limit} can be obtained from the power system operators to account for the uncertainties in the network. The power available for EV charging is then given by

$$p_j^{\text{available}} = p_j^{\text{limit}} - p_j^{\text{load demand}} \quad \forall j = 1, 2, 3, \dots, 48 \quad (3.19)$$

where subscript j represents each half-hour interval in the next 24 hours period. The initial and final SOC's required are obtained from the distance traveled by personal vehicles in Singapore [14]. The authors of [30] used the vehicle usage data to determine that the distance travelled by the personal vehicles will follow a normal distribution. In this paper, the energy required/km for different types of EVs is also used for calculating the initial and final SOC's. The arrival time and departure time of EVs are assumed to be normally distributed over 18:30 hours and 07:30 hours respectively with a standard deviation of 30 minutes. The above information is consistent with the data given by Land transport Authority of Singapore [96].

The final required SOC is generally around 90-100% as the EV users will prefer to charge their EVs to the desired SOC when the cost of electricity is lowest (off-peak period). Using the final required SOC of previous day, the distance travelled by the EVs (both obtained from stochastic samples), energy required/km, the initial SOC is calculated.

Thus, the uncertainties in the initial and final SOC's of the EVs are accounted into the simulations. An EV system consisting of three EVs having 7kWh battery capacity, three EVs having 24kWh battery capacity, and nine EVs having 16kWh battery capacity (total 15 EVs) is considered in this research. The number 15 is obtained by considering the ratio of personal vehicles to population in Singapore [30] and 33% EV penetration. Different battery capacities are considered to ensure that the impact of all the priority parameters on EVs with different battery capacities and average daily energy requirement can be analyzed precisely. It is important to have different types of battery capacities as it has huge influence on all the priority criteria. The battery capacities used in the thesis are the standard ones available in EV market such as Smart ED, Nissan Leaf, Mitsubishi i MiEV, Renault Twizy, Renault Kangoo Z.E., etc.

3.3.1 Power Coordinated Charging (PCC)

The PCC proposed in this research is a priority based dynamic charge scheduling. The algorithm considers $p_j^{available}$ and the power limits of EVs as the constraints for determining the EV charging power schedule (CPS). Each row of the CPS matrix gives the power allotted for the next 48 half-hour intervals of one EV that is connected to the smart grid network through an EV charging station. The CPS matrix is given in the form

$$CPS_{n,48} = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,48} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,48} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n,1} & p_{n,2} & \cdots & p_{n,48} \end{bmatrix} \quad (3.20)$$

where $p_{EV,i}^{min} \leq p_{i,j} \leq p_{EV,i}^{max}$ and $\sum_{i=1}^n p_{i,j} \leq p_j^{available}$

$p_{i,j}$ is the power allotted to the i^{th} EV for charging its battery on the j^{th} half-hour interval, $p_{EV,i}^{max}$ and $p_{EV,i}^{min}$ are the maximum and minimum power limits respectively based on the power handling capabilities of the EV charger and EV batteries. The amount of power

allotted to each EV depends on its priority value ρ_i . If α_i^x is priority criteria due to different parameters, then the value of ρ_i is given by

$$\rho_i = \sum_{x=1}^3 \alpha_i^x \quad \forall i = 1, 2, 3, \dots, n \quad (3.21)$$

As a first step the value of $p_{i,j}$ is initialized to

$$p_{i,j} = \frac{E_{req,i}}{N_{req,i}} \quad (3.22)$$

where $E_{req,i}$ is the minimum energy required for charging the i^{th} EV up to the desired SOC. It is verified whether the value is within the power limits of EV. If $\sum_{i=1}^n p_{i,j} > p_j^{available}$,

, then the $p_{i,j}$ of the EV with minimum value for ρ_i is set to zero and the procedure is repeated until $\sum_{i=1}^n p_{i,j} \leq p_j^{available}$. The flowchart of PCC charge scheduling is shown in

Figure 3.4. If $\sum_{i=1}^n p_{i,j} < p_j^{available}$, then the remaining power is allotted based on the following equation:

$$p_{i,j} = p_{i,j} + \frac{(p_j^{available} - \sum_{i=1}^n p_{i,j}) * \rho_i}{\sum_{i=1}^n \rho_i} \quad (3.23)$$

This will ensure that the power is allotted in proportion to the priority value and the variance in the priority values of EVs is reduced during the interval. If $\sum_{i=1}^n p_{EV,i}^{max} < p_j^{available}$, maximum power is allotted to all EVs. If the above condition is not satisfied and if the power allotted to any EV violates the $p_{EV,i}^{max}$ constraint, the difference between $p_{i,j}$ and $p_{EV,i}^{max}$ is allotted to the EV with highest value for ρ_i .

Figure 3.4 Flowchart for the algorithm used in PCC

This step is repeated for all 48 intervals, and the power allotted to each EV depends on $p_j^{available}$ and priority value of each EV. The priority values change dynamically after each half-hour interval based on the estimated status of EVs. Thus variance reduction as well as improvement in the SOC status happens simultaneously in all intervals.

3.3.2 Time Coordinated Charging (TCC)

The TCC charge scheduling also considers $p_j^{available}$ and $p_l^{EV,i}$ as the power constraints for obtaining the EV charging time schedule (CTS). The charging status of the i^{th} EV on the j^{th} half-hour interval is given by the CTS matrix in the form

$$CTS_{n,48} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,48} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,48} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,48} \end{bmatrix} \quad (3.24)$$

where $x_{i,j} = \begin{cases} 0, not\ charging \\ 1, charging \end{cases}$

and $\sum_{i=1}^n x_{i,j} * p_l^{EV,i} \leq p_j^{available}$

$x_{i,j}$ is the control signal broadcasted to the EV charging station to charge or discharge the battery. The control signal for each EV connected to a charging station is represented by a corresponding row in the CTS matrix for the next 48 half-hour intervals. The sequence in which an EV is allowed to charge depends on the priority value of EVs.

The flowchart of EV charge scheduling algorithm (TCC) is shown in Figure 3.5. The EV charging schedule matrix is initialized to a zero matrix after determining the $p_j^{available}$. The modification of the EV charging schedule matrix values which determines the EVs allowed to be charged during each interval is executed in the next step based on the priority values of the EVs. It is verified whether the constraint $\sum_{i=1}^n x_{i,j} * p_i^{EV} \leq p_j^{available}$ is satisfied after addition of each EV. This step is repeated for all the 48 intervals. The

priority value of each EV, the power limits of EV (if any) and $p_j^{available}$ during the charging period determine the number of EVs that are allowed to be charged in a given interval. The priority values not only change dynamically during every half-hour intervals based on the current status of the EVs but also during the scheduling process based on the expected status of the EVs. The EV charge scheduling algorithm along with real-time demand response ensures that the power limits are never violated.

Figure 3.5 Flowchart for the algorithm used in TCC

3.4 Impact of Priority Criteria on Chargeability and Fairness

It is important to analyze the impact of each priority criterion as well as the impact of various combinations of different priority criteria on the chargeability of the EVs to the required SOC and fairness in the allocation of charging time/energy. The analysis can serve as a guideline while selecting different parameters as priority criteria for any scheduling algorithm. In addition, the requirement for weighted priority criteria is also evaluated and optimal weights required for each case are determined. The analysis which

determines the impact of different criteria with their corresponding weights is vital for tuning the performance of the scheduling algorithms. However, such studies are not yet available in literature. As onset of smart grid will provide a large data which is earlier unavailable, the proposed data-driven simulations are an attractive option. The use of data-driven simulations is an effective solution for evaluation of EV charging strategies. Furthermore, it is feasible to accurately evaluate the overall performance of both the charging strategies, namely TCC and PCC. The analysis is carried out using stochastic building load demand and EV charging demand.

Data-driven simulations offer a wide variety of advantages. Updating the model parameters to account for the changes due to ageing is one of the major advantages. Furthermore, scaling up the system to account for new additions is relatively simple. The effectiveness of data-driven simulations and controller design using data-driven modeling has been studied by many authors [36]-[39]. However, in this research, the data-driven simulations are used for evaluating and comparing the performance of different charging strategies of EVs with different combination of priority criteria. The impact of all possible combinations of the three priority criteria which are widely used in literature is studied in this research.

A prospective residential smart grid network in Singapore will consist of a few high-rise HDB buildings connected together. It is assumed that a typical residential smart grid network will serve about 450 residential units. Hence stochastic load demand data is generated using the method explained in Section 3.3. Using the stochastic load demand data of the smart grid network and load demand data of the EVs, the scheduling process is carried out. The estimated SOC is obtained at the end of scheduling process. The scheduling process is carried out using individual priority criterion and various combinations of different priority criteria as listed in Table 3-2. The probability that an EV is not charged to the desired SOC is used for analyzing the impact of each of the three priority criteria and their different combinations. The analysis is carried out for both TCC and PCC charging strategies. Table 3-2 illustrates the overall probability of an EV not being charged to the desired SOC with different priority criteria. It can be observed from Table 3-2 that in case of TCC the probability that an EV is not charged is lowest at 0.0653 when only slack time is used as priority criterion. Whereas, the probability that an EV is not charged is highest at 0.1264 when SOC and allotted time are used as priority criteria. Furthermore, it can be observed that whenever SOC is used along with any of the other

two priority criterion, the probability that an EV is not charged increases, e.g., when slack time is used as the only priority criterion, the probability that an EV is not charged is 0.0653, but when it is used along with SOC, the probability increases to 0.0804. It can also be observed from Table 3-2 that in case of PCC, the probability that an EV is not charged is not significantly affected by the choice of priority criteria and the probability value is between 0.0217 and 0.0269. Furthermore, the probability that an EV is not charged is considerably less in PCC due to better utilization of the available power $p_j^{available}$. However, the overall probability that an EV is not charged just gives the overall performance of the scheduling algorithm and does not give the complete picture of the impact of different priority criteria on individual EV.

Hence, detailed analyses of the percentage of failure for each EV with reference to the total number of charging events are presented in Figures 3.6 and 3.7. It can be observed from Figures 3.6 and 3.7 that using SOC as one of the priority criteria (4 out of 7 cases) results in reduction of failures with decrease in battery capacity and energy requirement (i.e., EV1, EV2 and EV3). The result can be correlated by taking an example of two EVs having same SOC but different battery capacity, i.e., 7kWh and 24kWh. Since the SOC is the same for both the EVs, equal priority value for α_i^l is obtained from (3.12). Hence, equal resources, i.e., either equal charging time or equal charging power or both will be allotted. With equal resources (say 3kW power for 30 minutes), the EV with 7kWh battery capacity will be charged to a higher SOC value compared to the EV with 24kWh battery capacity.

Table 3-2 Overall probability of an EV not being charged with TCC and PCC

Priority criterion/criteria	TCC	PCC
	Probability that an EV is not charged	Probability that an EV is not charged
SOC + Slack time +Allotted time	0.0705	0.0217
Allotted time	0.1187	0.0268
Slack time + Allotted time	0.0891	0.0220
Slack time	0.0653	0.0269
SOC	0.1148	0.0231
SOC + Allotted time	0.1264	0.0223
SOC + Slack time	0.0804	0.0245

Using allotted time as one of the priority criteria (4 out of 7 cases) also results in similar phenomenon as observed from Figures 3.6 and 3.7. This is due to the fact that EVs which have higher allotted time/energy will have lesser value for α_i^3 as given by (3.14). With the same amount of allotted time/energy, an EV with lower battery capacity will be charged to a higher SOC value compared to an EV with higher battery capacity. However, the degree of reduction due to SOC is not the same as allotted time which can be seen from Figures 3.6 and 3.7. Using slack time (total 4 out of 7 cases) as the priority criterion results in opposite effect compared to the other two priority criteria, i.e., the number of failures reduces with increase in battery capacity and energy requirement (i.e., EV13, EV14 and EV15). This is because EVs with higher battery capacity and higher energy requirement will have low value for slack time and hence higher priority value for α_i^2 which is given by (3.13).

Figure 3.6 Percentage failure for different EVs in PCC while using different priority criteria

In order to ensure that all EVs are treated with absolute fairness, the number of failures should be in proportion to the energy requirement. Hence to verify whether the reduction of failures as a result of (3.12) and (3.14) for EVs with lower battery capacity and lower energy requirement is balanced by the reduction of failures as a result of (3.13) for EVs with higher battery capacity and higher energy requirement, the results have to be compared based on fairness index value FI_i of each EV.

$$FI_i = \frac{N_{F,i}/N_{FT}}{\overline{E_{R,i}} / \sum_{i=0}^n \overline{E_{R,i}}} \quad (3.25)$$

where $N_{F,i}$ is the number of failures of the i^{th} EV, N_{FT} is the total number of failures of all EVs, and $\overline{E_{R,i}}$ is the average energy requirement of the i^{th} EV. If the priority criteria used are absolutely fair to all EVs, then the FI_i value will be equal for all EVs. Hence, the results are compared based on the FI_i values.

Figure 3.7 Percentage failure for different EVs in TCC while using different priority criteria

The FI_i values of all the seven case scenarios for both TCC and PCC are shown in Table 3-3. It can be observed from Table 3-3 that the FI_i value varies over a wide range for all the seven case scenarios and for both TCC and PCC charging strategies. For example, in case of TCC when all the three priority criteria are used, the minimum value of FI_i is 0.033 for EV1, EV2 and EV3, whereas the maximum value is 1.426 for EV14. The reason is that the amount of preference given by a particular priority criterion to a particular type of EV is not equal to the amount preference given by other priority criterion, e.g., the amount of preference given by allotted time/SOC to EVs with lower battery capacity and lower energy requirement is not equal to the amount of preference given by slack time to EVs with higher battery capacity and higher energy requirement. The differences between the maximum and minimum values are also shown in Table 3-3 to illustrate the variations in fairness. It is to be noted from last row (Max-Min) of Table 3-3 that when SOC and slack time are used as priority criteria for TCC, minimum variations in FI_i values are obtained. However, the difference in values (Max-Min) is as high as 0.633. In case of PCC, minimum variations in FI_i values of 0.429 (Max-Min) are obtained when

slack time and allotted time are used as the priority criteria. By comparing the FI_i values (Max-Min) of TCC and PCC, it can be inferred that the FI_i values are not only affected by the chosen priority criteria, but also by the charging strategy used. In case of PCC, when SOC is used as the priority criterion, the minimum value of FI_i is 0.619 for EV3 as compared to 0.021 for EV1 in TCC. However, the maximum value for the same scenario in TCC is 1.645 for EV14 and 1.203 for EV6 and EV8 in PCC. This implies that the values of FI_i are spread over a wide region in case of TCC, whereas they are concentrated to a comparatively small region in case of PCC.

Table 3-3 Fairness Index before using Weights

	TCC						PCC					
	SOC + Slt + Alt	Alt	Slt + Alt	Slt	SOC	SOC + Alt	SOC + Slt	SOC + Slt + Alt	Alt	Slt + Alt	Slt	SOC
EV1	0.033	0.048	0.092	3.677	0.021	0.022	0.676	0.513	1.697	0.767	3.940	0.662
EV2	0.033	0.053	0.090	3.542	0.023	0.019	0.594	0.526	1.599	0.784	3.845	0.631
EV3	0.033	0.057	0.088	3.401	0.025	0.018	0.622	0.527	1.556	0.767	3.928	0.619
EV4	0.437	0.289	0.468	0.874	0.325	0.282	0.679	0.856	1.167	0.869	0.935	0.785
EV5	0.814	0.511	0.891	0.902	0.706	0.641	0.923	1.076	1.190	1.075	0.890	1.024
EV6	1.335	0.637	1.283	0.925	1.349	1.369	1.189	1.208	1.262	1.171	0.851	1.203
EV7	1.252	0.802	1.305	0.917	1.324	1.396	1.227	1.211	1.238	1.185	0.851	1.202
EV8	1.309	1.115	1.270	0.953	1.369	1.414	1.205	1.229	1.166	1.196	0.849	1.203
EV9	0.803	0.799	0.816	0.953	0.694	0.610	0.969	1.054	1.009	1.053	0.883	1.061
EV10	0.813	0.964	0.820	0.911	0.734	0.620	0.991	1.076	0.898	1.038	0.876	1.045
EV11	0.850	1.054	0.848	0.940	0.711	0.611	0.925	1.079	0.796	1.058	0.893	1.033
EV12	0.811	0.985	0.820	0.932	0.709	0.598	0.952	1.094	0.654	1.062	0.885	1.047
EV13	1.111	1.226	1.093	0.580	0.969	0.925	1.013	0.874	0.574	0.859	0.547	0.887
EV14	1.426	1.808	1.382	0.509	1.645	1.755	1.073	0.940	0.811	0.911	0.523	0.971
EV15	1.396	1.726	1.367	0.513	1.593	1.738	1.076	0.934	0.884	0.914	0.519	0.973
Max-Min	1.393	1.760	1.294	3.168	1.624	1.737	0.633	0.716	1.123	0.429	3.369	0.584

Notes:

1. Slt – Slack time 2. Alt – Allotted time/energy

3.4.1 Weighted Priority Criteria

To overcome the unequal preference given by each priority criterion towards a particular type of EV and ensure equal degree of fairness to all EVs, weighted priority criteria are to be used as proposed in [41], [44] and [69]. Hence the priority value of each EV ρ_i in (3.21) is to be modified as

$$\rho_i = \sum_{x=1}^3 w_i \alpha_i^x \quad \forall i = 1, 2, 3, \dots, n. \quad (3.26)$$

where w_i is the weight given to each priority criterion. It can be seen that the value of w_i can be tuned to obtain any kind of performance. The values of w_i is optimized using the proposed data-driven simulations and a second layer of optimization which minimizes the variance in FI_i values. The algorithm starts with unity value for all weights and modifies the values based on FI_i of the different EVs. For example, it can be observed from simulations without weights that if SOC is used as priority criterion then EVs with lower battery capacities will have low FI_i values. Hence the value of w_i corresponding to SOC is reduced.

The changes in the w_i values corresponding to slack time will be vice versa of SOC. This is essential for robust scheduling operation of EVs. However, the FI_i values do not change significantly for the cases where only one priority criterion is used, as the priority values for all EVs change proportionately with the weights. Simulation results for a different choice of w_i values, i.e., w_i values other than 1 are presented in Table 3-4 for both TCC and PCC charging strategies. Simulation results for FI_i using $w_i=0.5$ are given for the cases where individual priority criterion is used. It shows that in spite of using weights, FI_i values do not change significantly in such cases. It can be observed from last row (Max-Min) of Table 3-3 and Table 3-4 that with proper choice of w_i the fairness index values of all EVs can be brought close to the same value.

Also the difference between the maximum and minimum values of FI_i in both the charging strategies is reduced significantly for all the cases except where individual

priority criterion is used, e.g., in the case where SOC and slack time are used with weights as shown in Table 3-4, the difference between the maximum and minimum values is reduced by 55% ($= \frac{0.633 - 0.285}{0.633} * 100$), i.e., 0.633 in last row (Max-Min) of Table 3-3 to 0.285 in last row (Max-Min) of Table 3-4 (TCC). This shows that equal degree of fairness can be given to each and every EV, and using multiple priority criteria provides the flexibility to tune the fairness index. It can be seen from last row (Max-Min) of Table 3-3 and last row (Max-Min) of Table 3-4 that when all the three criteria are used in TCC, the reduction in difference between the maximum and minimum values is 78% ($= \frac{1.396 - 0.307}{1.396} * 100$).

This implies that increase in number of priority criteria used will result in increase of flexibility and ease in tuning the weights to obtain desired performance. It can also be observed that presence of complementing priority criteria (SOC and slack time or slack time and allotted time) results in higher reduction of the difference between the maximum and minimum values. If the priority criteria used are having similar characteristics (SOC and allotted time), negative weights are required for one of the priority criteria. Similar reduction in difference between the maximum and minimum values can be observed in PCC and also by comparing last row (Max-Min) of Table 3-3 and last row (Max-Min) of Table 3-4.

For example, in the similar case as in TCC where SOC and slack time are used with weights as shown in Table 3-4, the difference between the maximum and minimum values is reduced by 79% ($= \frac{1.606 - 0.335}{1.606} * 100$), i.e., 1.606 in last row (Max-Min) of Table 3-3 to 0.335 in last row (Max-Min) of Table 3-4 (PCC). It can also be seen from last row (Max-Min) of Table 3-3 and last row (Max-Min) of Table 3-4 that when all the three criteria are used in PCC, the reduction in difference between the maximum and minimum values is only 52% ($= \frac{0.716 - 0.347}{0.716} * 100$). This implies that the increase in number of priority criteria used has no significant effect in PCC. It can also be seen from Tables 3-3 and 3-4 that though same priority criteria are used, the FI_i values are different for TCC and PCC. As a result, the values of weights are not the same for TCC and PCC

because the FI_i values are not only affected by the chosen priority criteria, but also by the charging strategy used. The choice of w_i depends on the objective of the scheduling operation. The weights given in Table 3-4 are based on the objective to have approximately equal FI_i value for all EVs. For a different objective, the value of w_i will change accordingly.

Table 3-4 Fairness Index after using Weights

	TCC							PCC						
	SOC + Slt +Alt	Alt	Slt+ Alt	Slt	SOC	SOC + Alt	SOC + Slt	SOC + Slt +Alt	Alt	Slt+ Alt	Slt	SOC	SOC + Alt	SOC + Slt
W ₁	0.3	0	0	0	0.5	2.95	0.55	0.7	0	0	0	0.5	2.0	1.40
W ₂	1.0	0	1.39	0.5	0	0	0.88	1.0	0	1.0	0.5	0	0	0.50
W ₃	0.2	0.5	0.44	0	0	-0.45	0	0.7	0.5	0.9	0	0	-0.45	0
EV1	0.999	0.053	1.096	3.677	0.023	0.691	1.172	0.858	1.669	0.968	3.899	0.650	0.848	0.895
EV2	0.998	0.057	1.139	3.621	0.024	0.742	1.117	0.861	1.621	0.920	3.980	0.648	0.860	0.853
EV3	0.993	0.059	1.122	3.573	0.022	0.643	1.104	0.874	1.581	0.983	3.873	0.618	0.860	0.859
EV4	0.956	0.309	0.978	0.866	0.306	1.414	0.927	0.857	1.138	0.867	0.929	0.808	1.218	0.968
EV5	0.985	0.474	0.937	0.902	0.731	1.141	0.977	1.080	1.227	1.041	0.885	1.017	1.115	1.072
EV6	1.202	0.667	1.195	0.931	1.382	0.692	1.149	1.171	1.237	1.166	0.831	1.207	1.041	1.169
EV7	1.193	0.772	1.227	0.937	1.410	0.735	1.199	1.181	1.209	1.168	0.848	1.227	1.051	1.154
EV8	1.219	1.069	1.215	0.935	1.374	0.711	1.186	1.186	1.151	1.167	0.848	1.236	1.031	1.169
EV9	0.940	0.796	0.928	0.921	0.711	1.143	0.956	1.065	1.009	1.048	0.907	1.032	1.128	1.091
EV10	0.950	0.969	0.940	0.916	0.704	1.156	0.963	1.047	0.931	1.047	0.883	1.026	1.097	1.061
EV11	0.914	1.060	0.980	0.908	0.731	1.125	0.956	1.049	0.788	1.018	0.888	1.056	1.122	1.085
EV12	0.962	1.043	0.936	0.915	0.703	1.164	0.946	1.081	0.664	1.037	0.880	1.018	1.132	1.063
EV13	0.912	1.222	0.942	0.567	0.973	1.278	0.901	0.839	0.570	0.864	0.541	0.883	0.909	0.834
EV14	0.999	1.737	0.963	0.501	1.591	0.795	0.947	0.886	0.819	0.896	0.524	0.970	0.814	0.851
EV15	0.996	1.803	0.979	0.513	1.562	0.760	0.916	0.887	0.889	0.897	0.524	0.961	0.819	0.864
Max- Min	0.307	1.750	0.291	3.176	1.540	0.723	0.285	0.347	1.099	0.303	3.456	0.609	0.403	0.335

Notes:

1. Slt – Slack time 2. Alt – Allotted time/energy

3.5 Summary

In this chapter, an Artificial Neural Network (ANN) based model for predicting the charging profiles of EVs was proposed. The result of the predicted charging profile was shown for a typical EV. The MAPE obtained was around 4.5% for most of the cases. The model was able to track the changes in the power consumption due to battery aging and degradation. The changes in power consumption due to battery aging and degradation may not have significance if only a few EVs are considered. However, in the case of urban cities like Singapore where the EVs will be charged in groups (typically 50-100), the changes in power consumption will have significant effect. The predicted charging profiles were used to determine the unscheduled load demand for a group of EVs.

Scheduling is the vital component of coordinated EV charging strategies and priority criteria used for scheduling have a huge impact on their performance. In this chapter, a dynamic EV charge scheduling algorithm was proposed for TCC and PCC. The impact of various combinations of different priority criteria, namely SOC, slack time and allotted time/energy on the chargeability of EVs and their fairness index was studied for both types of coordinated EV charging. The overall performances of coordinated EV charging methods employing various combinations of different priority criteria were evaluated using data-driven simulations and results were presented. The results indicated that the choice of priority criteria has significant impact on the chargeability of EV charge scheduling algorithms. The analysis on the fairness component while using different priority criteria emphasizes the necessity for using weighted priority criteria. It was also observed that using multiple criteria with weights ensures better flexibility for achieving higher fairness among EVs with different battery capacities. The weights obtained for different cases of the simulations have demonstrated that the values of weights are different for different charging strategies. Hence, the weights are to be tuned appropriately using the proposed data-driven simulations for improving the performance of the scheduling algorithms used for EV charging. The analysis can serve as a guideline for selecting different parameters as priority criteria and their weights required for making any scheduling algorithm robust.

CHAPTER 4 APPLICATIONS OF DYNAMIC EV SCHEDULING: VEHICLE TO GRID CAPACITY ESTIMATION AND DEMAND RESPONSE MANAGEMENT

In this chapter, an algorithm for half-hourly vehicle to grid (V2G) capacity estimation using real-time EV scheduling and demand response management using real-time EV scheduling is presented. The concepts explained in this chapter are based on author's publications [44], [47] and [110].

4.1 V2G Capacity Estimation Method

An aggregated number of EVs provide a platform for smart energy storage (SES) in buildings which can be used during periods of maximum demand or high electricity price as well as for leveling the intermittent outputs of renewable energy sources (RESs). However, the vehicle to grid (V2G) capacity varies over time based on the availability of the EVs and their individual state of charge (SOC). Hence a real-time V2G capacity estimation is important for utilizing EVs as SES efficiently. In this research, an algorithm for half-hourly V2G capacity estimation using real-time EV scheduling is proposed. The algorithm is implemented as part of the Building Energy Management System (BEMS). The BEMS uses forecasted building load demand without EVs and predicted charging profiles of the EVs connected to the building for estimating the V2G capacity. The estimated V2G capacity and the availability of RESs are considered by the BEMS to schedule the EV charging/discharging. The proposed algorithm is applied to study two case scenarios using BEMS on residential and commercial buildings in Singapore. The results obtained clearly show that a group of EVs connected to any high-rise building can be effectively used as a distributed storage system.

The TCC presented in Chapter 3 is modified for application of V2G capacity estimation in a building. The modified algorithm is shown in Figure 4.1. The algorithm utilizes day ahead half-hourly forecasted load demand without EVs p_j^L (which corresponds to the $p_j^{loaddemand}$ in equation (3.15)), predicted EV charging profile $p_t^{EV,i}$, predicted output of RESs p_j^{RES} , power demand constraint p_{CC} , and number of allotted charging intervals

$n_j^{EV,i}$ for each $EV_{lapsed,j,i}$ EV. Half-hour intervals in a day are represented by subscript $j = 1, 2, 3 \dots 48$. If k is the total number of charging intervals required for charging a particular EV, then subscript $l = 1, 2, 3 \dots, k$. EV ID is given by the superscript i and it takes the values $1, 2, 3 \dots, n$, where n is the total number of EVs. The charge schedule is updated every half hour considering 30-minute electricity price intervals. The forecasted load demand taking RES outputs into consideration is given by

$$p_j^{PD} = p_j^L - p_j^{RES} \quad \forall j = 1, 2, 3, \dots, 48. \quad (4.1)$$

$p^{average}$ corresponds to P^{limit} in equation (3.17). The algorithm considers the contracted capacity or maximum power demand limit p_{CC} and the average power used for achieving a smooth valley filling $p^{average}$ for obtaining the EV charging schedule (CTS)

The values of $x_{i,j}$ in CTS are obtained by subjecting the total load demand after considering RESs and EVs p_j^{TD} to the following conditions:

- a) the additional load due to EV charging does not exceed $x\%$ of p_{CC} ; and
- b) p_j^{TD} does not exceed $p^{average}$ by $y\%$ of $p^{average}$.

The first constraint is to ensure that the EVs scheduled for charging will not exceed the maximum power demand limit and thus overload the power system. The second constraint is required to achieve a smooth valley filling and higher energy efficiency [40]. Therefore, each half-hour interval in the EV charge scheduling (i.e., a total of 48 intervals) will have an optimum number of EV charging. Furthermore, 24-hour scheduling helps to spread the EV load without violating owner's satisfaction and comfort. The value of x should be selected such that the total demand of the building is always within the maximum power demand limit. The actual value of x can be determined based on either heuristic approach or statistical data on load demand. The choice of x is determined based on the ability of the demand response algorithm used by building energy management system (BEMS) to curtail the total load demand below p_{CC} . For example, in a building 80% of p_{CC} can be used as the limit for controlling the EV demand while 85% of p_{CC} can be used as the limit for controlling HVAC demand and

90% of p_{CC} can be used as the limit for shedding other interruptible loads. Hence if the EVs are scheduled for charging when the total demand is greater than 80% of p_{CC} , the charging will be interrupted by the demand response algorithm. The second condition that p_j^{TD} cannot be greater than $y\%$ of $p^{average}$ to ensure that the EVs are charged to desired SOC and a smooth valley filling is achieved. A typical example as shown in Figure 4.2 is used to explain the above condition. If 10% of $p^{average}$ is considered as the additional limit for scheduling the EV charging, all the EVs can be charged to desired SOC and a smooth valley filling is achieved during off-peak period. Furthermore, the margin to exceed 80% of contracted capacity is sufficiently large so that EV charging will not be interrupted. 10% of $p^{average}$ is considered to cater for charging more EVs without exceeding 80% of contracted capacity during off-peak period.

The sequence in which an EV is added to p_j^{TD} depends on the priority value of EVs. In the algorithm various dynamic priority criteria are used for scheduling the EV charging. The flowchart of EV charge scheduling algorithm used is shown in Figure 4.1. In the first step the load demand without EVs is obtained using (4.1). In the second step the load demand due to the addition of EV load is obtained from (3.9), (3.10) and (3.18). This is then superimposed on the load demand without EVs obtained from (4.1) and the total load demand with EVs is obtained. The average load demand is calculated for whole charging period using (3.11) and (3.17) in the next step. The initialization of EV charging schedule matrix is to a zero matrix is carried out in fourth step. The modification of the EV charging schedule matrix values which determine the EVs allowed to be charged during each interval is executed in the fifth step. This step is repeated for all the 48 intervals. The priority value of each EV, the power limits (if any) and the average power during the charging period determines the number of EVs that are allowed to be charged in a given interval.

Figure 4.1 Dynamic scheduling algorithm used for estimation of V2G capacity

Figure 4.2 Typical load curve and EV charging during off-peak period

Notes:

1. $p^{average}$ is the average power during charging period considering the total load demand with EVs, i.e., average power (building load demand + EV load demand).
2. p_{CC} is the maximum power demand limit.

V2G is a concept in which energy from EV is supplied to grid. Various other terminologies such as Vehicle to Home (V2H) and Vehicle to Building (V2B) are also commonly used. V2G can be used for many applications such as to supply additional energy during periods of maximum demand or high electricity price. However, as V2G requires using up a fraction of battery life, EV users may be reluctant to enter into an agreement with building operators unless there are considerable monetary or convenience benefits.

The V2G concept also enables the utilization of EV batteries as storage for levelling the intermittency of RESs. For utilizing EV batteries as SES, V2G capacity has to be estimated in real-time for efficient and optimum control of the V2G operation. The aggregation process is also governed by the amount of power and energy that the EVs can supply during any given interval. The V2G capacity estimation can be based on many factors/constraints, but the two most important factors to be considered in V2G capacity estimation are discussed below .

i) Maximum and Continuous V2G Power

The ratings of the power electronic converters used for charging and discharging the EV batteries impose the limits on maximum V2G power p_i^{v2gmax} and continuous V2G power $p_i^{v2gcont}$. Generally the power ratings of the EV batteries are considerable higher than the ratings of their power electronic converters. This implies that p_i^{v2gmax} and $p_i^{v2gcont}$ are not constrained by the battery power ratings, e.g., the continuous power of Mitsubishi MiEV's battery is 80kW and the continuous power of its power electronic converter is 2.5kW [34]. p_i^{v2gmax} and $p_i^{v2gcont}$ are basic necessity for determining the cumulative power that a group of EVs can supply during a given interval.

ii) V2G Energy Available

Ability of the system to charge the EV to its required SOC at departure so as to satisfy the travel needs of the owner is crucial. Hence, the chargeability and drivability of the EVs is to be ensured before utilizing the EVs for auxiliary functions such as V2G. The V2G energy available $E_i^{v2gav'lable}$ from each EV depends on current state of charge $SOC_i^{current}$, desired final state of charge SOC_i^{final} , and minimum required state of charge SOC_i^{min} at the end of current interval for charging the EV to SOC_i^{final} before departure time. The flowchart of the V2G capacity estimation algorithm is shown in Figure 4.3. The chargeability and drivability of the EVs can only be ensured by the EV charge scheduling algorithm, and hence the scheduling algorithm forms the basic block for V2G capacity estimation.

In addition to the priority criteria described in Chapter 3, priority criterion based on V2G power supplied (χ_i) representing the priority parameter due to V2G power/energy

Figure 4.3 Flowchart for V2G capacity estimation algorithm

supplied by the EV is also considered in this simulation. The higher the number of intervals in which the EV supplied V2G power, the higher will be the priority for charging the EV as shown in (4.2). This parameter is essential for achieving higher customer's satisfaction. $N_{v2g,i}$ is the equivalent number of half-hour time intervals during which the EV is supplying power. $N_{total,i}$ is the equivalent number of half-hour time intervals required for charging EV from initial to desired SOC.

$$\chi_i = \left(\frac{N_{v2g,i}}{N_{total,i}} \right) \quad (4.2)$$

The V2G capacity estimation is carried out at the beginning of every half-hour interval. It can be seen from Figure 4.3 that the V2G capacity estimation has two processes, one every 30 minutes and the other one every minute. The first process which is executed every 30 minutes calculates the minimum SOC required for each EV at the end of the current interval so that the EVs can be charged completely before departure. The scheduling algorithm shown in Figure 4.1 is used to determine the chargeability of the EVs considering the calculated minimum required SOC as the current SOC of the next interval. If the estimated SOC at the last departure interval is less than the desired SOC, the minimum required SOC is then increased by $r\%$ (say 5%) and the whole process is repeated. All the above four steps are shown under the condition '*Time=xx: 30 or xx: 60*' in Figure 4.3. Meanwhile, the second process which is executed every minute tracks the amount of energy supplied during the current interval and updates the results as shown under the condition '*Time=xx: xx: 59*' in Figure 4.3.

The maximum energy that can be supplied by each EV during a given interval is

$$E_i^{v2g\ max} = P_i^{v2g\ cont} * \tau \quad (4.3)$$

The time factor τ has a value of 0.5 as 30-minute interval is considered and changes accordingly with the changes in the time period of the interval. The SOC_i^{min} is calculated to start the estimation process. SOC_i^{min} is the minimum required SOC at the end of current half-hour interval for achieving SOC_i^{final} of each EV before their respective departure interval. SOC_i^{min} is initialized such that maximum energy can be supplied during the given interval and the chargeability of EV is verified using EV scheduling. If the

chargeability is violated, then SOC_i^{min} is iteratively increased and verified using EV scheduling until the chargeability is not violated. (4.4) and (4.5) are then used to calculate the V2G energy that the EV can supply in the current half-hour interval.

$$E_i^{v2g} = (SOC_i^{current} - SOC_i^{min}) * C_i \quad (4.4)$$

where C_i is the energy capacity of the i^{th} EV.

$$E_i^{v2gav'lable} = \begin{cases} 0, & E_i^{v2g} \leq 0 \\ E_i^{v2g}, & 0 < E_i^{v2g} < E_i^{v2gmax} \\ E_i^{v2gmax}, & E_i^{v2g} \geq E_i^{v2gmax} \end{cases} \quad (4.5)$$

$E_i^{v2gav'lable}$ in (4.5) is restricted to E_i^{v2gmax} , which is the limitation imposed by the power electronic converters used for charging and discharging the EV batteries. Using the V2G energy available, the V2G power available can be determined by

$$p_i^{v2g} = \frac{E_i^{v2gav'lable}}{\tau_l} \quad (4.6)$$

where τ_l is the actual time for which the V2G power is supplied or can be supplied during the given interval. p_i^{v2g} will vary depending on the value of τ_l . However it is limited to p_i^{v2gmax} and is governed by the short time rating of the power electronic converter and the battery. Therefore, the continuous power that can be provided through V2G is given by

$$p_i^{v2gcont} * \tau = p_{i,j}^{v2g} * \tau_l \quad (4.7)$$

The estimated V2G capacity for the current half-hour interval updates every minute in order to account for the actual energy and power supplied during the particular interval. The total V2G energy and V2G power available from a group of EVs is given by (4.8) and (4.9) respectively.

$$E^{v2gtotal} = \sum_{i=1}^n E_i^{v2gav'lable} \quad (4.8)$$

$$p_j^{v2gtotal} = \sum_{i=1}^n p_i^{v2g} \quad (4.9)$$

The feedback on charging status is received only once after each 30-minute interval and the V2G estimation using dynamic scheduling is executed only at xx:30 or xx:00 hours (e.g., 13:30 or 14:00 hours), which avoids any positive feedback on the estimation during the charging. Subsequently every minute estimation at xx:xx:59 (e.g., 13:30:59) within a particular interval is performed to determine only the real-time V2G power without re-estimation using EV scheduling. The re-estimation using EV scheduling will only occur at the end of the interval. Hence the stability issues related to positive feedback to the EV charging are avoided.

4.1.1 Case Study 1: High-rise Residential Buildings

Nearly 80% of residential buildings in Singapore are the HDB high-rise buildings. The characteristic of the EV fleet connected to a HDB building is such that the number of EVs available during office hours is comparatively less than the number of EVs available in the early morning, evening and night. This is due to the fact that most of the EV owners will drive their EVs to work in the morning and back to home in the evening. Therefore, the EV fleet connected to a HDB building has the potential to supply V2G power during the early morning peak hours (06:30 to 07:30 hours) and evening peak hours (19:00 to 21:30 hours). The energy available from EVs with higher SOC (due to comparatively lower traveling distance than the maximum travel range) can be used to shave a portion of the building load demand during evening peak hours or to charge other EVs which require immediate charging. The EVs then can be charged using cheaper electricity available during the night off-peak period (21:30 to 06:00 hours) and a part of the stored energy (additional energy above the required SOC at departure) can then be used to supply V2G power to reduce the building load during the early morning peak hours. In this case study, the V2G capacity is estimated for a HDB building with a contracted capacity of 300kW and a typical EV fleet as shown in Table 4-1.

Table 4-1 is formulated based on the consideration that the average distance traveled by a personal vehicle in Singapore follows a normal distribution with an average of 55km and a standard deviation of 10km [14] and [96]. The arrival time and departure time of the EVs are assumed to be normally distributed over 18:30 hours and 07:30 hours respectively with a standard deviation of 30 minutes. It can be observed from Table 4-1

that the average initial SOC of the EVs is around 50-55% and the average required SOC is very high, around 90%. This is because the EV users will prefer to charge their EVs to the desired SOC when the cost of electricity is very low (off-peak period).

The V2G capacity estimated for half-hour intervals from 18:00 to 08:00 hours along with the number of EVs connected to the BEMS of the residential building during each interval is shown in Figure 4.4(a). The average current SOC and required SOC of all the EVs are also shown in Figure 4.4(b). The minimum SOC for discharging (V2G) is fixed at 25% such that no EV will be discharged below 25% of SOC. Generally, EVs are not discharged below 15-20% to ensure higher battery life. Having additional 5-10% energy will ensure that the EV can be driven to nearest fast charging station under emergency conditions. The minimum SOC required for each EV at 20:30 hours is calculated at 20:00 hours using the method discussed in Section 4.1 and has an average of 37.25% for 14 EVs. The 15th EV is not considered in the V2G estimation as it arrives after 20:00 hours. Then the minimum SOC required for all EVs is substituted in (4.4)-(4.6) to obtain the V2G power of 45kW.

Table 4-1 Typical EV Fleet of a HDB Building

EV ID (<i>i</i>)	Capacity (kWh)	Initial SOC (%)	Desired SOC (%)	Arrival Time (hr)	Departure Time (hr)
1	24	77.92	90	18:25	07:20
2	24	65.42	80	19:39	07:16
3	24	65.96	95	18:59	07:55
4	24	50.29	85	17:30	07:21
5	24	53.13	85	16:35	07:41
6	24	44.58	80	18:12	07:50
7	24	53.88	90	18:51	07:24
8	24	61.71	95	19:02	07:49
9	24	50.33	90	19:50	07:02
10	24	49.63	90	19:01	07:57
11	24	53.21	95	16:56	07:11
12	24	43.21	85	18:32	07:15
13	24	48.25	95	18:45	08:17
14	24	48.25	95	18:56	07:18
15	24	39.04	95	20:05	06:41

The minimum SOC allowed for the EVs will also have an impact on V2G capacity, i.e., higher minimum SOC will result in lower V2G capacity. It can also be observed from Figure 4.4(a) that the V2G power available increases from 10kW to 45kW with the arrival of new EVs between 18:00 and 20:00 hours. Although the discharging (V2G) starts at 19:30 hours, an increase in the V2G capacity is observed between 19:00 and 20:00 hours due to the arrival of additional EVs with higher current SOC. It can be seen that the V2G power available starts to decrease after 20:00 hours and reaches a value of about 14kW at 21:30 hours. Then the V2G power available increases after 23:00 hours with increase in average current SOC due to charging. The V2G power reaches the maximum of 48kW at 00:30 hours. The V2G power decreases between 20:00 and 21:30 hours because of the decrease in average current SOC as a result of discharging operation and can be observed from Figure 4.4(b). The average current SOC does not change between 21:30 and 23:00 hours as the EVs are neither charged nor discharged. The above condition is due to the fact that the EVs will not be charged during peak period and ensures a smooth valley filling.

Figure 4.4 (a) Estimation of V2G power and number of EVs for residential building;
(b) Average current SOC and average required SOC

It can be observed from Figure 4.4(b) that the EVs are charged to their desired SOC at 05:00 hours with a smooth valley filling. However, the EVs are charged beyond their desired SOC from 05:00 to 06:30 hours in order to have a higher and stable V2G power during the morning peak hours. Charging beyond the average required SOC will also result in smoother valley filling and early morning peak shaving. Figure 4.5 illustrates the building load demand with and without the EVs charging/discharging. The smooth valley filling between 23:00 and 06:30 hours is controlled by the dynamic scheduling, e.g., at 23:30 hours the value of $p^{average}$ is calculated using (3.17) and has a value of 169.92kW. The load demand without EVs at 23:30 hours is 159.79kW, hence only EV1-EV8 is charged as deduced by (3.24) so that the total load demand is less than 110% of 169.92kW. The same procedure also applies for other two cases. It can be seen that an average peak shaving of 10.62% during evening peak hours (19:00 to 21:30 hours) and 9.34% during morning peak hours (06:30 to 07:30 hours) can be achieved using V2G in high-rise residential buildings. Furthermore, the higher V2G capacity during late night

Figure 4.5 Peak shaving and valley filling with EVs

period between 00:00 and 05:00 hours is highly suitable for mitigating the intermittency of wind energy.

It is important to note that the results obtained for the above case study is sensitive to the randomness in number of EVs and their availabilities. Furthermore, the battery capacities of the EVs have a significant impact on the V2G capacity, e.g., if the battery capacities of the EVs in Table 4-1 are changed such that 3 EVs have 7kWh, 3 EVs have 24kWh, and the rest are 16kWh, the V2G capacity during evening peak period between 19:00 and 21:30 hours reduces from 45kW to 15kW. With a higher standard deviation for arrival of EVs, the V2G capacity is lower during each interval of evening peak period.

4.1.2 Case Study 2: Office Buildings

The algorithm is applied to study a case scenario using BEMS employed in an office building. It is assumed that the building is equipped with 70kWp solar PV installed on its rooftop. The maximum power $P_i^{v2gcont}$ for an EV is fixed at 3.4kW corresponding to level II charger of Nissan Leaf. In an EV fleet connected to an office building the number of EVs available during office hours (08:30 to 17:30 hours) is significantly higher than the number of EVs available in non-office hours (17:30 to 08:30 hours). So the EVs are used as SES for the solar PV from 08:30 to 17:30 hours. Hence, the V2G capacity of EVs parked at the office building is significantly large during the office hours and offers feasibility for using EV batteries as SES for intermittent solar PV system installed in the office building. The predicted output of a solar PV system rated at 70kWp during the office hours from 08:30 to 17:30 hours is shown in Figure 4.6. The predicted solar PV output is obtained using irradiance data of a typical day in Singapore. The average solar PV output $p^{ave\ pv}$ for the period of operation can be determined using the method explained in [109].

Figure 4.6 Predicted output of 70kWp solar PV system

The amount of V2G power required to cater for the intermittency of solar PV is based on the difference between the actual solar PV output power and average solar PV output power as given by

$$p_j^{v2g \text{ required}} = p_j^{act \text{ pv}} - p^{ave \text{ pv}} \quad (4.10)$$

where $p_j^{act \text{ pv}}$ and $p_j^{v2g \text{ required}}$ are the actual solar PV output and V2G power required during the intervals $j=1, 2, 3 \dots 48$. When $p_j^{v2g \text{ required}}$ is negative, the V2G power available from the EVs will be used to balance the power shortage and when $p_j^{v2g \text{ required}}$ is positive, surplus solar PV output power will be used to charge the EV. It is assumed that no EV is allowed to discharge (V2G) below 50% of SOC to ensure that minimum required SOC at departure can be achieved for all the EVs. However, the possibility that the available V2G power is less than the power deficit of solar PV is nearly remote. To clearly show the difference between using EVs as SES for solar PV and using EVs as SES along with solar PV for peak shaving, similar system parameters used in case study B of [44] where an office building with a contracted capacity p_{CC} of 270kW and a typical EV fleet as shown in Table 4-2 are considered.

Table 4-2 is obtained by considering the average travel distance of 55km for Singapore's personal vehicles [14] and it is assumed that the distance travelled by personal vehicles follows a normal distribution with a standard deviation of 10km [14] and [96]. The arrival time and departure time of the EVs are assumed to be normally distributed over 08:30 hours and 17:30 hours respectively with a standard deviation of 30 minutes. In an EV fleet connected to an office building, the EVs would have completed only one way travel which is approximately half of the average per day travel distance. This is depicted in Table 4-2, according to which the average initial SOC is 70.74%. Furthermore, the initial SOC and the minimum desired SOC at departure of EVs have the same value as the EV users will allow the building operators to use the battery capacity but will be reluctant to have lower SOC at departure to avoid range anxiety. However, the maximum SOC to which the EVs can charge is set to 100% so as to enable complete utilization of the solar PV power and EVs can be charged beyond the minimum desired SOC at departure during power surplus which can be later utilized during power shortage.

$p_j^{act\ pv}$, $p_j^{v2g\ required}$, and $p_j^{v2g\ total}$ between 08:30 and 17:30 hours are shown in Figure 4.7 while the average current SOC and the minimum required SOC of all the EVs are shown in Figure 4.8. From Figure 4.7, it can be inferred that during the morning hours,

Table 4-2 Typical EV Fleet of an Office Building

EV ID (i)	Capacity (kWh)	Initial SOC (%)	Minimum Desired SOC (%)	Arrival Time (hr)	Departure Time (hr)
1	24	83.96	83.96	08:12	17:30
2	24	72.08	72.08	08:34	17:16
3	24	80.48	80.48	07:59	17:40
4	24	65.52	65.52	07:58	17:13
5	24	68.00	68.00	08:02	17:59
6	24	61.23	61.23	09:01	17:14
7	24	70.52	70.52	08:39	17:48
8	24	75.52	75.52	08:37	17:14
9	24	69.10	69.10	08:14	17:50
10	24	69.10	69.10	07:58	18:13
11	24	75.17	75.17	08:10	17:05
12	24	64.10	64.10	08:28	17:34
13	24	72.33	72.33	08:07	17:18
14	24	70.56	70.56	08:43	18:08
15	24	63.48	63.48	07:58	17:51

i.e., from 08:30 to 10:30 hours, $p_j^{act\ pv}$ is less than the estimated $p^{ave\ pv}$ due to comparatively less solar irradiation. Hence, the EV batteries are used to supplement the power deficit in comparison to $p^{ave\ pv}$. It can also be observed that $p_j^{v2g\ required}$ is well within the limits of $p_j^{v2g\ total}$ as the EVs are generally charged to the maximum possible SOC using cheaper power available during the off-peak hours, i.e., from 19:00 to 06:00 hours, and also as the EVs have travelled only half of their daily travelling distance. For example, the $p_j^{v2g\ required}$ from 10:00 to 10:30 hours is 14.29kW but $p_j^{v2g\ total}$ during the same interval is significantly higher at 51.41kW. This is mainly due to the fact that the possibility of charging the EVs to desired SOC is very high as sufficient time is available for charging the EVs before departure. From Figure 4.8, the decrease in average SOC during the time period of 08:30 to 10:30 hours illustrates the discharging of EV batteries during this time interval. Whereas, from 10:30 to 15:00 hours due to strong solar irradiation, $p_j^{act\ pv}$ is greater than the estimated $p^{ave\ pv}$ and hence the EV batteries are used to store the surplus power generated by solar PV. This subsequently increases the average SOC during the time period between 10:30 and 15:00 hours as shown in Figure 4.8. However, when $p_j^{act\ pv}$ becomes lesser than $p^{ave\ pv}$ from 15:00 to 16:00 hours possibly due to some cloud covering, the EV batteries which were sufficiently charged during the period from 10:30 to 15:00 hours yields a $p_j^{v2g\ total}$ of 51.41kW which is much higher compared to $p_j^{v2g\ required}$ of 3.27kW from 15:00 to 15:30 hours and 6.05kW from 15:30 to 16:00 hours respectively. The operation of the EV batteries during the period from 16:00 to 17:00 hours is similar to the charging operation from 10:30 to 15:00 hours while the operation of the EV batteries during the period from 17:00 to 17:30 hours is similar to the discharging operation from 15:00 to 16:00 hours. Comparing Figures 4.7 and 4.8 to the Figures 6(a) and 6(b) of [44], it can be clearly seen that the depth of discharge of EV batteries when used as SES for solar PV is less compared to the depth of discharge when it is used as SES for peak shaving. Since the life of battery is inversely proportional to the depth of discharge, using EV batteries as SES for solar PV is beneficial in terms of prolonging EV battery life cycle compared to using it for peak shaving. Furthermore, the V2G capacity is also higher and much more stable when EV batteries are used as SES for solar PV.

Figure 4.7 Solar PV intermittency and V2G capacity

Figure 4.8 SOC profiles of EVs connected for V2G operation

Using the same system parameters as in the previous case study, if a sudden loss of solar PV power for a particular time period is implicated, then the importance of using scheduling for V2G capacity estimation can be realized. For example, let us assume that PV power is lost between 13:00 and 15:00 hours due to sudden weather condition such as heavy rain as highlighted in Figure 4.9. The changes in $p_j^{v2gtotal}$ which can be observed from Figure 4.9 show that $p_j^{v2gtotal}$ drops drastically after supplying $p^{ave\ pv}$ of 34.03kW, i.e., the estimated average power from solar PV for three continuous interval between 13:00 and 14:30 hours. From 14:30 to 15:00 hours, although the required V2G power is 34.03kW, only 6.8kW is available from the EVs.

This is due to the fact that the average current SOC has reduced to 52.89% as shown in Figure 4.10, which means that in order to ensure chargeability of the EVs before departure, no more than 6.8kW can be supplied as V2G power. Without a charge scheduling algorithm, if 34.03kW instead of 6.8kW was also supplied for the period from 14:30 to 15:00 hours, the EVs will not be able to charge up to the desired SOC before departure and thus cause inconvenience and dissatisfaction to EV owners.

Figure 4.9 Solar PV intermittency and V2G capacity under sudden solar PV loss

Figure 4.10 SOC profiles of EVs connected for V2G operation under sudden solar PV loss

4.1.3 Comparative Analysis

The accuracy of V2G estimation with and without dynamic scheduling of EVs is used as a criterion for comparison. The accuracy of V2G estimation is evaluated by calculating the probability of charging the EVs to the desired SOC. The average deviation of actual SOC from desired SOC at departure will also give a good measure for the accuracy of V2G estimation. The analysis is carried out using stochastic forecasted building load demand and EV charging demand for Case Study 1. The proposed V2G estimation method is compared with fixed minimum SOC limited estimation method [89], [90] and plug-in probability based estimation method [67], [91] which do not employ dynamic scheduling of EVs. The fixed minimum SOC limited estimation method also uses the minimum SOC limit of 25% employed by the proposed V2G estimation method in Case Study 1. The plug-in probability based estimation method determines the probability of EVs connected to the building based on the normally distributed arrival time and departure time as discussed in Case Study 1.

The comparison of the accuracy of V2G estimation of the proposed method and the other two methods is performed for three scenarios, namely EVs discharging from 21:00 to 22:00 hours, 01:30 to 02:30 hours and 05:30 to 06:30 hours for Case Study 1. These three scenarios are selected such that the time remaining before departure is different for each scenario and hence the effect of the time remaining for departure on the accuracy of V2G estimation can be determined. Table 4-3 illustrates the accuracy of V2G estimation for the proposed V2G estimation method, fixed SOC limited estimation method and plug-in probability based estimation method. It can be observed from Table 4-3 that the accuracy of V2G estimation in the other two methods is significantly affected by the time remaining before departure, e.g., in scenario 3 of case study 1, the probabilities of charging the EVs to desired SOC are only 0.3485 and 0.3852 for the fixed minimum SOC limited estimation method and plug-in probability based estimation method respectively. However, the proposed V2G estimation method can achieve a probability of 0.9827 for charging the EVs to desired SOC. Furthermore, the average deviations of actual SOC from desired SOC at departure are as high as 8.57% and 7.72% for the fixed minimum SOC limited estimation method and plug-in probability based estimation method respectively. In comparison, the proposed V2G estimation method achieves a lower deviation of 0.87%. This indicates that the proposed V2G estimation method can improve the accuracy of V2G estimation. The accuracy of the proposed V2G estimation method is also not affected by the time remaining before departure.

Table 4-4 illustrates similar comparison for Case Study 2. The comparison is carried out to illustrate the impact of discharging in subsequent intervals which is a common phenomenon when the PV power is lost due to unexpected weather condition. The

Table 4-3 Comparison of the Accuracy of V2G Estimation for Three Different Methods

Scenario	Proposed V2G Estimation Method		Fixed SOC Limited Estimation Method		Plug-in Probability Based Method	
	<i>P1</i>	<i>P2 (%)</i>	<i>P1</i>	<i>P2 (%)</i>	<i>P1</i>	<i>P2 (%)</i>
1	0.9833	-0.53	0.9158	-0.66	0.8976	-3.09
2	0.9846	-0.74	0.9090	-1.40	0.9044	-1.92
3	0.9827	-0.87	0.3485	-8.57	0.3852	-7.72

Notes:

1. *P1* - Probability of charging the EVs to the desired SOC's
2. *P2* - The average deviation of actual SOC from desired SOC at departure

comparison is performed using stochastic load demand and stochastic EV demand. Three scenarios, namely scenarios 1, 2 and 3 where EVs are discharged to supply V2G power from 10:00 to 10:30 hours, 13:00 to 13:30 hours and 16:00 to 16:30 hours respectively are considered for the comparison. It can be observed from Table 4-4 that the estimation accuracy of the methods which do not employ scheduling of EVs decreases with increasing number of subsequent discharging intervals. It can be seen that in scenario 3, the average deviation of actual final SOC from desired final SOC when the EVs are not charged are higher at 3.74% and 3.05% for the fixed minimum SOC limited estimation and plug-in probability based estimation methods respectively compared to only 0.92% for the V2G capacity estimation using dynamic scheduling. This indicates that the accuracy of V2G capacity estimation using dynamic scheduling is not affected by the number of subsequent discharging intervals as well as the time of estimation.

4.2 Pre-emptive Demand Response Management

As discussed in Chapter 2, the methods available in literature for control of EV mainly focus on using a single EV available in a residential building as interruptible load (in fixed power charging mode) or flexible load (in variable power charging mode) where the priority of the EV is combined with other residential loads [97], [102] and [103]. The method proposed in this research for using EVs in DRM focuses on combining several EVs available in commercial buildings to behave as both flexible and interruptible load using fixed power charging mode. Furthermore, the proposed dynamic priority criteria used for EVs participating in DRM is a novel approach which is applicable for managing EV load demand in commercial buildings. The proposed method will also ensure higher

Table 4-4 Comparison of V2G Estimation Accuracy

Scenario	Proposed V2G Estimation Method		Fixed SOC Limited Estimation Method		Plug-in Probability Based Method	
	<i>P1</i>	<i>P2 (%)</i>	<i>P1</i>	<i>P2 (%)</i>	<i>P1</i>	<i>P2 (%)</i>
1	0.9848	-0.65	0.9223	-0.98	0.9189	-0.95
2	0.9852	-0.83	0.9266	-0.93	0.9011	-0.97
3	0.9803	-0.92	0.9147	-3.74	0.9095	-3.05

Notes:

1. *P1* - Probability of charging the EVs to the desired SOC's
2. *P2* - The average deviation of actual SOC from desired SOC at departure

degree of fairness to the EV owners as the EV with highest probability to charge before departure is shed first when the DRM for EV is invoked. The DRM is implemented as a part of Building Energy Management System.

In this research, EVs are considered as the lowest priority load that will be shed first before shedding any other interruptible loads. This is because temporary discontinuity of EV charging will not have significant impact on the EV owner's satisfaction and comfort provided that the owner's required SOC at departure can be achieved. The dynamic EV charge scheduling algorithm ensures that the EV charging will be scheduled dynamically every half-hour in order to ensure the required SOC at departure can be achieved despite EV load shedding during a particular interval. Furthermore, the chargeability of the EVs is estimated and only if a particular EV can be charged to desired SOC, the EV is considered as an interruptible load. The flowchart of the algorithm proposed for determining the chargeability of the EVs is shown in Figure 4.11. The algorithm is similar to the one proposed in Section 4.1 with minor modifications. The chargeability matrix is given by

$$Cd_n = \begin{bmatrix} cd_1 \\ cd_2 \\ \vdots \\ cd_n \end{bmatrix} \quad (4.11)$$

where $cd_i=1$ if the i^{th} EV can be charged to the desired SOC before the departure interval even if its charging is interrupted in the current interval and $cd_i=0$ if the EV cannot be charged to the desired SOC.

Figure 4.11 Flowchart of algorithm used for determining the chargeability of EVs

It can be seen from Figure 4.11 that the chargeability of the EVs is determined at the end of every minute. The scheduling algorithm shown in Figure 4.1 is used to determine the chargeability of the EVs considering the current SOC ($SOC_i^{current}$) as the current SOC of the next interval (SOC_i^{next}), i.e., the EV is not charged further in the current interval. If the estimated SOC ($SOC_i^{m_i}$) at the last departure interval (m_i) is less than the desired SOC, then the value of cd_i is set to '0' otherwise it set to '1'.

The load shedding priority of an EV that is being charged during one particular half-hour interval is obtained based on three priority parameters described in Chapter 3. First two parameters are closely associated with owner's satisfaction and comfort. When the values of these parameters are high, it ensures higher possibility of achieving the owner's

required SOC at departure. Therefore, higher SOC and slack time will yield lower load shedding priority for a particular EV. This is because even if the EV is shed for demand response, the EV can still be charged up to its required SOC in the subsequent half-hour intervals. The third parameter relates to the amount of charging time already allocated to a particular EV. The load shedding priority of a particular EV will be lower if the EV has been granted higher amount of charging time in order to ensure fairness to all EV owners.

The proposed DRM program will invoke shedding of the lowest priority EV when the building current load demand P_{CD} exceeds $x\%$ of contracted capacity/demand limit (CC/DL). This process repeats for the next lowest priority EV if P_{CD} continues to exceed $x\%$ of CC/DL until all EVs that are being charged have been shed. However, when the building returns to its normal operation and P_{CD} reduces to less than $z\%$ of CC/DL, the EVs that have been shed previously will be allowed to charge based on their priority values. In this case, the highest priority EV among the EVs that are not being charged will be allowed to start charging. The lowest priority EV for one particular half-hour interval j is obtained from the selection of the EV with the minimum priority value from all EVs that are being charged during the interval j . Similarly, the highest priority EV for one particular half-hour interval j is obtained from the selection of the EV with the maximum priority value from all EVs that are not charged during the interval j . The selection of the lowest and highest priority EV can be represented by

$$i = \begin{cases} \sigma_{\min}(\rho_{i,j}), & P_{CD} > x\% \text{ of } CC / DL \\ \sigma_{\max}(\rho_{i,j}), & P_{CD} < z\% \text{ of } CC / DL \end{cases} \quad (4.12)$$

for $i = 1, 2, 3, \dots, n$ where n is the total number of EV charging stations installed in the building. Equation (4.12) returns the EV number where $\sigma_{\min}(\rho_{i,j})$ and $\sigma_{\max}(\rho_{i,j})$ denote the selection process of the EV having the lowest and highest priority values respectively, and subscripts 'min' and 'max' represent the propositional formula to select the EV with the minimum and maximum priority values respectively. For example, if there are 5 EVs connected to the building, namely EV1, EV2, EV3, EV4 and EV5 with specific priority values of 2, 4, 3, 6 and 1 respectively, $\sigma_{\min}(\rho_{i,j})$ will select EV5 as it has the lowest priority value and $\sigma_{\max}(\rho_{i,j})$ will select EV4 as it has the highest priority value. The control signal sent by the BEMS to the circuit breaker at the EV charging station to start or stop charging according to the DRM program is given by

$$x_{i,j} = \begin{cases} 0, & P_{CD} > x\% \text{ of } CC / DL \\ 1, & P_{CD} < z\% \text{ of } CC / DL \end{cases} \quad (4.13)$$

where “0” and “1” represent the circuit breaker “OFF” and “ON” status respectively, j represents one half-hour interval in a day and i is the EV number.

In order to assess the performance of the proposed DRM program, individual case studies are conducted to study the capability of the proposed DRM program to ensure that P_{CD} is always maintained below CC/DL. In order to evaluate the accuracy of the developed mathematical models, the analytical results obtained using the mathematical models presented in this paper are compared with the simulation results obtained using the computer simulation models of the BEMS. In the case studies the values of x , y and z parameters are considered as 80%, 90% and 50% respectively. For the forecasted DRM using EV charge scheduling, the case study presented uses a specific EV charge schedule derived based on the EV profiles given in Table 4-5 which is obtained based on a normal distribution with an average travel distance of 55 km and a standard deviation of 10 km [14] and [96]. Assuming that the working hours of the EV owners in a commercial building are from 08:30 to 18:00 hours, the arrival and departure of the EVs are varied randomly between 08:30 hours and 18:00 hours in the simulation in order to clearly observe the advantage of the proposed dynamic EV charge scheduling. The output of the dynamic EV charge scheduling at 09:30 hours based on the procedure discussed in Chapter 3 is given by

$$CS_{5,48} = \left[\begin{array}{cccccccccccccccc} 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & \dots & 0 \\ 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \end{array} \right] \left. \begin{array}{l} \text{EV 1} \\ \text{EV 2} \\ \text{EV 3} \\ \text{EV 4} \\ \text{EV 5} \end{array} \right\} \text{EV ID}$$

09:30 10:30 11:30 12:30 13:30 14:30 15:30 16:30 09:00

Time (hours)

Table 4-5 Parameters for Dynamic EV Charge Scheduling

EV ID (i)	Capacity (kWh)	Initial SOC (%)	Desired SOC (%)	Arrival Time (hr)	Departure Time (hr)
1	7	68.57	85	8:55	18:47
2	16	52.85	80	8:48	21:37
3	16	73.75	95	8:13	20:18
4	16	59.50	85	8:55	19:05
5	24	65.95	90	9:15	17:50

The chargeability matrix for 09:30 hours determined by the algorithm shown in Figure

4.11 is $Cd_5 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$. The value of cd_i is '1' for all EVs at 09:30 hours and it remains

same throughout the interval as sufficient time is available for charging. Hence the sequence of shedding depends solely on the priority values.

It can be seen that during the half-hour interval from 09:30 to 10:00 hours, EV 4 and EV 5 are allocated time for charging as the values of $x_{4,1}$ and $x_{5,1}$ are equal to 1. This is because based on the departure time of all the EVs, EV 5 actually has a shorter slack time available for charging compared to other EVs. On the other hand, EV 4 which has a longer slack time available for charging compared to EV 1 is allocated charging time during this interval as it has a larger charging requirement to fulfill before the departure time compared to EV 1. Also, it can be observed that EV 2 which arrived earlier than EVs 1, 4 and 5 is given the lowest priority for charging due to its smaller SOC requirement and longer slack time as it will depart last. It can also be seen that at most only three EVs are allocated charging time during one particular interval in order to ensure that the total building load will not exceed $x\%$ of CC/DL. However, the dynamic EV charge scheduling ensures that all five EVs are charged to their required SOC before their departure time.

Figures 4.12 and 4.13 show the capability of the dynamic EV charge scheduling DRM program to respond swiftly to unexpected lower and higher building load demand compared to the predicted load profile respectively. It can be observed that the analytical results obtained using the developed load models correspond well with the simulation

results. The analytical results are obtained from the model described in [47] and are given in Appendix A for reference. P_{others} is used as the control variable in the DRM analysis to decrease and increase P_{CD} to $z\%$ and $x\%$ of CC/DL respectively. As shown in Figure 4.12, with the decrease in P_{CD} to less than $z\%$ (in this case 50%) of CC/DL (i.e., 25kW) at 09:46 hours, the EV load is increased in steps taking into consideration the conditions that the additional load due to the EV charging violates the constraints explained on page 79 under Figure 4.1. It can be seen that only one EV is allowed to start charging at 09:46 hours without violating the conditions. In the event when other load demand P_{others} is reduced further at 09:52 hours, two more EVs are scheduled to start charging. This ensures proper resource utilization and higher charging efficiency as EVs are charged during low load period. The response can also be related to a scenario when the outputs of DERs such as solar PVs

Figure 4.12 Dynamic charge scheduling of EVs during low load period

Figure 4.13 Dynamic charge scheduling of EVs during high load period

4.3 Summary

The estimation of real-time V2G capacity of EVs is crucial for using EVs as distributed energy storage. In this chapter, an algorithm for estimating the real-time V2G capacity using dynamic EV scheduling for EVs connected to BEMS of a building was proposed. The algorithm was designed based on an accurate EV load model proposed in chapter 3. The model based scheduling approach ensures the chargeability of the EVs to the desired SOC's before departure while estimating the V2G capacity. The dynamic priority criteria used in the scheduling ensures fairness to each customer and optimizes customer satisfaction. The algorithm was tested using two different case studies and the results were discussed. It was found that the parameters such as contracted capacity, load demand, battery capacity, and arrival and departure times have a unique impact on the V2G capacity of the EVs. The proposed V2G estimation method was also compared with the fixed minimum SOC limited estimation method and plug-in probability based estimation methods which do not employ scheduling of EVs. It was observed that the proposed method improved the accuracy of V2G estimation and was not affected by the

time remaining before departure. The results showed that a group of EVs connected to any high-rise building which is common in densely populated cities can be effectively used as distributed energy storage. The real-time V2G capacity estimation ensures that the optimal amount of energy from EVs is utilized without affecting the requirements of EV users. In this chapter, a preemptive DRM for EVs as a part DRM program for commercial buildings to maintain the load demand within the contracted capacity or utility imposed demand limit was proposed. The DRM program utilizes building energy management system to execute different demand response techniques, dynamic EV charge scheduling and priority-based shedding of EV load is one part of the program.

CHAPTER 5 A METHODOLOGY FOR OPTIMIZING THE NUMBER OF ELECTRIC VEHICLES DEPLOYED UNDER A SMART GRID

In this chapter, an algorithm for estimating and optimizing the number of EVs that can be deployed under a smart grid is presented. A methodology for determining the power limits required for scheduling based on transformer's loss of life. The concepts presented in this chapter are based on author's publications [48], [49].

5.1 Introduction

As discussed in Chapter 1, electrification of transportation will significantly reduce the amount of greenhouse gas emissions and also improve the efficiency of the transportation sector dramatically. The biggest obstacle for the deployment of EVs is the range anxiety of the EV users [111]. A well-developed charging infrastructure will subsequently reduce the EV user's fear on running out of charge. A reduction in the user's range anxiety coupled with an increase of government incentivized programs will encourage many commuters to adopt EVs which are more environmental friendly. To ease the changeover, more EV charging stations should be installed. However, for promoting investment in the installation of EV charging stations, two important questions are to be answered i) how many charging stations should be installed, and ii) what is the cost and benefit to charging station's owner. Hence estimating the number of EVs that a given segment of smart grid can support and the number of charging stations required is the primary step in electrification of transportation.

In [112], the authors have estimated the percentage of EVs that can be deployed with current power generation capacity. In few studies such as [113], the total power generation requirements for a stipulated percentage of EV fleet have been estimated. However, no standard method has been proposed in the above papers for the process of estimation for EV deployment. Furthermore, the future power grid is expected to be more distributed as a result of increasing renewable energy penetration. In Singapore, high-rise buildings with solar PVs installed at the rooftops will be the basic block for such a

distributed power system. Hence a reliable method for estimating the number of EVs that can be connected to a smart grid segment such as high-rise buildings is crucial. Furthermore, with the progressive implementation of smart meters, large amount of data which were earlier unavailable will be available in future for analyzing and optimizing the performance of the grid.

In [49], a methodology for estimating the number of EVs has been proposed and the method is also applicable for distributed systems since capability of distribution transformer was considered for determining the limits. However, the above method has used solely a deterministic approach and has not considered the future increase of load demand. As discussed in Chapter 2, there are various studies conducted which analyses the impacts of EV charging on the power system parameters including voltage regulation, harmonics, power losses, equipment life, etc. These studies can be used to determine the constraints for estimating the number of EVs and hence the number of charging stations. Though there are various parameters, all the parameters converge down to the maximum additional power that can be supplied to EVs for charging. Hence the maximum additional power that can be supplied is taken as the primary constraint for estimating the number of EVs.

The installation of charging station will have a cascading effect on the future load and operation cost. Hence using deterministic samples of past/current load data will result in an inaccurate estimation. To overcome this disadvantage, estimated future load demands and stochastic calculations are used in this research. Stochastic calculations are used to account for the randomness in load demands. It is assumed that the information such as average, maximum, minimum, and variance of the load demands are available for the required period of estimation, i.e., 5 years. The load demands of Singapore [114] are scaled down and used for calculating the required parameters of future load demands. Monte-carlo simulations are used to generate the stochastic samples and calculate the spare energy available. The spare energy is then used for estimating the optimal number of EVs or charging stations by linear programming.

5.2 Methodology for Estimating Optimal Number of EVs

5.2.1 Load Demand Data and Spare Energy Calculation

5.2.1.1 Load Demand Data and Stochastic Samples

The proposed method requires information such as average, maximum, minimum, standard deviation, etc. on the future load demands. Singapore's load demands for the years 2005-2009 collected from [114] are scaled down to represent a high-rise building's load demand and considered as the future load demands for the years 2013-2017. A typical load demand with the corresponding power limits is shown in Figure 5.1. The load demand data is represented for 24 hours with 30 minute intervals given that Singapore power grid uses 30 minute electricity pricing.

$$p_n = (p_1, p_2, p_3, \dots, p_{48}) \quad (5.1)$$

where p_n is the load demand for any given day and p_i represents the load demand for i^{th} interval ($i=1, 2, 3, \dots, 48$).

The required information mentioned above is obtained from the 5-year load demand data and is gathered for three categories (for each half-hour interval) via monthly, week days

Figure 5.1 A typical scaled down load demand with power limits

and weekends. It is then used to generate a few thousand (N) independent and identically distributed (iid) random samples from the probability density function (PDF) of the load demand [115]. The samples are generated until the sample mean and variance converge to the average and variance obtained from the load demand data.

$$\overline{p_i} \approx \frac{1}{N} \sum_{k=1}^N p_i^k \quad (5.2)$$

$$\overline{\sigma_i^2} \approx \sigma_i^2 \quad (5.3)$$

For $i=1, 2, 3, \dots, 48$, $\overline{p_i}$ and $\overline{\sigma_i^2}$ are the mean and variance obtained from load demands, N is the number of samples generated, p_i^k is the k^{th} iid and σ_i^2 is the variance of generated samples. The load demand data is assumed to follow a normal distribution. The assumption of normality was verified by testing the load demand data using “Lillie test” [116]. Scaled down data of Singapore’s 13 years (1999-2011) load demands and 90 days load demand data collected from the Wee Kim Wee School of Communication and Information building in Nanyang Technological University (NTU) was used for the above verification. The pseudo-random samples are generated for each day of the upcoming 5 years. If the data did not follow any of the standard probability density functions (PDFs), then the pseudo-random samples can be generated using non-parametric methods.

5.2.1.2 Methodology for Spare Energy Calculation

The spare energy can be calculated by subjecting the generated iid to the pre-determined constraints. Maximum power that can be supplied during each interval is taken as the constraint in this research. Various parameters which can be used as the constraints are directly linked to the maximum power that can be supplied. Hence the constraint for spare energy calculation is of the form:

$$p_n^{limit} = (p_1^{limit} , p_2^{limit} , p_3^{limit} , \dots , p_{48}^{limit}) \quad (5.4)$$

where p_n^{limit} are the power limits for any given day and p_n^{limit} represents the power limit for i^{th} interval ($i=1, 2, 3, \dots, 48$). The power limits for a given day depend on various factors including voltage regulation, harmonics, power losses, equipment life, availability of renewable energy sources, rating of the equipment, contracted capacity,

cost of electricity, etc. The method discussed in Section 5.4 can be used to determine the power limits using transformer life as the constraint. The same method can also be used to calculate the power limits using other constraints. Apart from the power limits, the availability or the presence of EVs needs to be considered, e.g., in residential buildings the EVs will be parked only from evening to morning (say intervals 36 to 48 and 1 to 15 considering 00:00-00:30 hours as 1st interval) and similarly for office buildings the EVs will be parked only during office hours (say intervals 18 to 34). Hence the constraints on availability of EVs will also be considered while calculating the spare energy.

$$l \leq i \leq m \quad (5.5)$$

where l and m are the first and last intervals between which the EVs are available and $i=1, 2, 3, \dots, 48$. The expected spare energy for any given day is

$$E_{spare} = \frac{1}{N} \sum_{k=1}^N \frac{1}{2} \sum_{i=l}^m p_i^{limit} - p_i^k \quad (5.6)$$

E_{spare} is the spare energy available for integration of EV. p_i^{limit} are the power limits during the interval l to m and p_i^k is the power demand in i^{th} interval obtained using stochastic process. Similarly the expected spare energy can be calculated for all the days of the estimation period. Given the annual increase in the load demand, the expected spare energy will decrease every year. The decrease in the expected spare energy can be compensated by selecting higher p_n^{limit} or reducing the load demand (to account the renewable penetration) for subsequent years. If the estimate of future penetration of renewable energy is available, higher accuracy can be achieved. The algorithm used for calculating the spare energy is shown in Figure 5.2.

5.2.2 Optimizing (maximizing) the Number of EVs

The expected spare energy calculated is used as a constraint for optimizing (maximizing) the number of EVs that can be deployed under the given system (high-rise building). Based on the optimized number and type of EVs, the charging stations can be installed. The objective function is to maximize

$$\max_a f(a) = \sum_{i=1}^n x_i a_i \quad (5.7)$$

$$\max_a f(a) = \sum_{i=1}^n C_i x_i a_i \quad (5.8)$$

where a_i is the number of vehicles for each type (say, car, motorcycle, quad-cycle, moped, etc.) that is to be determined. x_i is the average energy required for the corresponding type of vehicles. i represents particular vehicle type, for example, a EV car or EV motorcycle. C_i is the cost per kWh for each category of vehicle. The objective function is to be subjected to constraints based on the percentage of each type of vehicles

$$\sum_{i=1}^n x_i a_i \leq E_{spare} \quad (5.9)$$

Figure 5.2 Flowchart of the algorithm used for calculating spare energy

$$a_i = \frac{k_i}{100} * \sum_{i=1}^n a_i \quad (5.10)$$

$$0 \leq a_i \leq \frac{E_{spare}}{x_i} \quad (5.11)$$

where $i=1, 2, 3, \dots, n$, k_i is the percentage of each type of vehicle and n is number of vehicle types. Along with percentage constraints, any other constraints such as the number of parking lots available can be imposed while optimizing the number of EVs. The average energy required/km for each type of vehicle [2]-[4] is shown in Table 5-1. Using daily average distance travelled by a specific group of vehicles, x_i can be determined for each category. In the case of Singapore, the daily average distance travelled by each type of vehicle can be obtained from [14]. The objective function for optimization can be modified to (5.8). The number of vehicles can be optimized to maximize the profit for charging station owners using C_i cost per kWh for each category of vehicle.

The proposed method is applied to a typical high-rise Housing Development Board (HDB) building in Singapore. The EVs connected to a typical high-rise residential building in Singapore will be charged during off-peak night hours, i.e., typically from 22:00 hours in the evening to 07:00 hours in the morning. Hence the range of values of l and m in (3.5) can be considered as 44 to 48 and 1 to 14 respectively. The factor for scaling Singapore's load demand to match the load demand of residential building is 18251 (5475.3MW/300kW), given that the peak demand of Singapore during the considered years was 5475.3MW. This is because a typical residential building in Singapore will have the peak demand around 300kW. The power limits during the

Table 5-1 Typical energy consumption of different types of EVs

Type of Vehicle	Energy Required/km (kWh)	Average Distance Travelled/day	Average kWh/day
E-car	0.2006	55	11.00
E-quad/tricycle	0.1003	55	5.52
E-motorcycle	0.0700	40	2.80

Table 5-2 Spare energy available for different power limits

Year	Charging Period Power Limits (kW)			Spare Energy Available (kWh)		
	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3
Year 1	220	225	230	79.92	124.92	169.92
Year 2	227	232	237	79.77	124.77	169.77
Year 3	235	240	245	70.36	115.36	160.36
Year 4	237	242	247	82.48	127.48	172.48
Year 5	238	243	248	79.39	124.39	169.39

charging period are varied as shown in Table 5-2 and the variations in the expected spare energy are also listed. The power limits can be selected using any of the constraints mentioned in Section 5.2.1.2 but using equipment life has many advantages [49]. Three different types of vehicles are considered and their corresponding x_i is shown in Table 5-1. The percentage constraints are varied and the corresponding results of optimization are obtained for expected spare energy of 78.38kWh (average of 5 years) and shown in Table 5-3. The selected spare energy is average of five years shown in Case 1 of Table 5-2.

It can be clearly observed from Table 5-2 that the increase of power limit from 220kW to 230kW results in a proportionate increase of the expected spare energy available from 79.92kWh to 169.92kWh for the first year. The same observation is applicable for other

Table 5-3 Optimized number of vehicles

Type of Vehicle	Scenario 1		Scenario 2		Scenario 3	
	k_i	a_i	k_i	a_i	k_i	a_i
E-car	60	6	37.5	4	25	3
E-quad/tricycle	15	1	37.5	4	50	6
E-motorcycle	25	2	25	3	25	3
Total	100	9	100	11	100	12

years too. It can also be observed from Table 5-3 that the use of lighter vehicles, e.g., use of EV-quad/tricycle in lieu of EV cars will facilitate more integration. For example, in scenario 1 the system can support 9 EVs for given power limits whereas in scenario 3 the same system can support 12 EVs for the same power limits as more E-quad/tricycles are used. Using lighter vehicles is ideal for dealing with congestion and also provides better efficiency in terms of energy required/km/person.

5.2.3 Validation of the Method Using EV Scheduling

The proposed method can be validated by superimposing the load demand of the estimated number of EVs on the building load demand for a substantial time period of 5 years. An EV scheduling method is required to manage the charging of EVs such that the constraints are not violated. In this research, the validation process is discussed for Case 1 in Table 5-3 with the EV scheduling algorithm which was discussed in detail shown in Chapter 3. The first step of the scheduling process is to calculate the load demand without EVs followed by the estimation of the load demand due to EVs using method discussed in Chapter 3. The estimated load demand due to EVs is then superimposed on the load demand without EVs to obtain the total load demand with EVs. In the next step, the average load demand during the charging period is calculated. Then the load demand of each EV is added to the building load demand in all the intervals where the EVs are available for charging. The number of EVs which is allowed to be charged depends on the power limits, average power during the charging period and priority value of each EV.

The iid for the distance travelled by each vehicle in any given day is obtained from the normal distribution whose mean is given by [14] and the standard deviation is assumed to be 10km. The estimated state of charge (SOC) is obtained at the end of scheduling process. The simulation for the given day is repeated until the iid generated satisfies the constraints given by (5.2) and (5.3). The simulation is repeated for a period of 5 years and the results are discussed below. The histogram of the difference between the desired final SOC and the estimated SOC at the time of departure for 5 years are shown Figure 5.3. It is observed that the frequency of the values which is less than ‘-5%’ is very low, whereas the frequency of the values is observed to be very high above ‘0%’. The higher frequency at

lower positive differences, i.e., '0%' to '10%' validates that the proposed method of estimation is accurate.

Figure 5.3 Histogram of the difference between the desired final SOC and the estimated SOC at the time of departure for 5 years

5.3 Cost-Benefit Analysis

Cost-benefit analysis for the installation of charging stations will not only demonstrate the benefits of charger installation to building owners but also act as guidelines for determining the price of electricity used for charging the EVs. The cost-benefit analysis for Case 1 in Table 5.3 is discussed below and the results are shown in Table 5.4. The installation cost of level 2 chargers from Bosch is around S\$25,000 and it can be used to charge 2 EVs simultaneously. Hence four such chargers are required for charging 6 E-cars and 1 E-quad/tricycle. The installation cost of the chargers required for E-motorcycles is considered as S\$10,000 and can charge two E-motorcycles. Hence one such charger is required for charging two E-motorcycles. Therefore, the total installation cost for the charging infrastructure is around S\$110,000. The price of electricity is considered as S\$0.28/kWh [117]. The petrol price is taken as S\$2.1/liter and the average mileage/liter of each vehicle category is used to calculate the running costs for conventional vehicles. The estimated running costs of conventional car, quad/tricycle and motorcycle are S\$9.82, S\$6.5, S\$3.15 respectively [14], [117]. The corresponding values for EVs are highlighted in Table 5.4, i.e., No 7 for E-car and No 10 for both E-quad/tricycle and E-motorcycle. By using the parity prices for electricity, i.e., S\$0.9 for E-cars and S\$1.2 for both E-quad/tricycle and E-motorcycle, the number of days required

Table 5-4 Cost-benefit analysis for Case 1

No	Electricity Selling (S\$)	Average Income per Day (S\$)			Total Profit per Day (S\$)	Number of Days to Recover Investment
		E-Car	E-quad/Tricycle	E-motor Cycle		
1	0.3	3.30	1.66	0.84	1.54	71317
2	0.4	4.40	2.21	1.12	9.25	11886
3	0.5	5.50	2.76	1.40	16.97	6483
4	0.6	6.60	3.31	1.68	24.68	4457
5	0.7	7.70	3.86	1.96	32.39	3396
6	0.8	8.80	4.42	2.24	40.10	2743
7	0.9	9.90	4.97	2.52	47.81	2301
8	1.0	11.00	5.52	2.80	55.53	1981
9	1.1	12.10	6.07	3.08	63.24	1739
10	1.2	13.20	6.62	3.36	70.95	1550
11	1.3	14.30	7.18	3.64	78.66	1398
12	1.4	15.40	7.73	3.92	86.37	1273
13	1.5	16.50	8.28	4.20	94.09	1169

to recover the investment will be 2,151 days (6 years). However, with the expected increase in the price of fossil fuels, integration of more renewable energy sources and advancements in technology, the number of days required for recovering the investment cost would decrease drastically.

5.4 Determination of P^{limits}

There are numerous methods in the literature that can be used to determine the impact of electrification on transportation; however, few studies have estimated the number of EVs that can be deployed with current power generation capacity [112], or estimated the total power generation requirement for a stipulated EV fleet percentage [113]. In this research, a methodology for estimating the capability of distribution transformers to support the EV fleet is determined. This is highly important as each distribution transformer has different capacities and characteristics that determine the amount of EVs it can handle at any given time. The distribution transformers are the weakest links of a power system because of their relatively low capacity and low operating voltage. Due to the additional load created by EVs, the distribution transformers are relatively stressed more than any other equipment in the distribution system [22]. Hence estimating the capability of distribution transformers to support EVs is important in order to determine the capability of whole system. The loss of life (LOL) of the distribution transformer is an important factor to consider as it is directly related to reliability and economics of the system [60]. Any premature/unexpected failure of the distribution transformer is not only associated with replacement cost but also the revenue loss due to supply interruption. A study on the capacity of the transformer will provide the amount of additional EV loads that can be supported by the transformer such that the additional load has minimal effect on the transformer's life expectancy. The decision on the amount of LOL allowed will be taken by the power system operators.

A methodology is proposed in this research for determining the amount of additional energy the transformer can supply for an allowed additional loss of life. Table 5-5 describes the transformer parameters used for simulations. A 1,000 kVA transformer is considered to represent the transformers supplying power to HDB buildings.

Table 5-5 Transformer parameters

Life of transformer (Hours):	180,000
Ambient temperature (°C):	30
Rated load (kVA):	1,000
Ratio of full load loss and no load loss:	4.5
Empirical constant M:	0.7
Empirical constant N:	0.7
Top oil temperature rise over ambient at rated load (°C):	45
Hotspot temperature rise over top oil at rated load (°C):	35
Oil thermal time constant for rated load (Hours):	4.89

In order to obtain the maximum energy that can be supplied, the LOL of the transformer's insulation is analyzed. The load demand obtained from Section 5.2.1.1 is used in the simulations.

Since the life of the transformer's insulation depends on its average load during a particular period rather than the instantaneous load, approximation of the actual load curve into time intervals is needed. The approximation of the load curve is obtained by

$$L = \sqrt{\frac{L_1^2 t_1 + L_2^2 t_2 + L_3^2 t_3 + \cdots + L_n^2 t_n}{t_1 + t_2 + t_3 + \cdots + t_n}} \quad (5.12)$$

where L_1, L_2 , etc are the various load steps in percentage per unit, in actual power (kVA) or in current (A), and N is the total number of time intervals considered. t_1, t_2 , etc are the respective durations of these loads in minutes.

The intervals for the load approximation are decided based on a number of factors. Firstly, the starting time of the off-peak period of the load curve, which is approximately 22:00 hours, is considered. Secondly, the approximate time required for the transformer insulation to cool down to the desired temperature is taken to be approximately 2 hours.

Thirdly, the average charging time required for the EVs is taken to be around 6-10 hours to reach 100% state of charge (SOC). Finally, the availability of the EVs for charging is also considered. The additional energy that the transformer can supply with the allowed LOL can be calculated using the algorithm as shown in Figure 5.4. The base LOL is calculated using the load demand and transformer LOL calculation. Following that the load demand in the interval in which the EVs are charged are increased in steps equal to 0.01% (can be varied based on the desired resolution) of the transformer's rated energy/day. The LOL is calculated and checked whether it is within the allowed limit of additional loss. The added energy is used to calculate the power limits

$$(P_{limits} = \frac{Total\ Energy\ Added}{Time\ in\ hours\ of\ the\ selected\ interval}) .$$

The transformer LOL is determined by

$$F_{AA} = \exp \left[\frac{1500}{383} - \frac{1500}{\Theta_H + 273} \right] \quad (5.13)$$

$$F_{EQA} = \frac{\sum_{n=1}^N F_{AA} \cdot n \cdot \Delta t_n}{\sum_{n=1}^N \Delta t_n} \quad (5.14)$$

$$(5.15)$$

F_{EQA}	is the equivalent aging factor for the total time period,
n	is index of the time interval, t,
N	is total number of time intervals,
F_{AA}	is aging acceleration factor for the temperature which exists during the time interval t_n
t_n	is time interval, hours,
Θ_H	is the winding hotspot temperature, °C.
%LOL	is the percentage loss of life

The winding hotspot temperature is calculated using the method explained in Annexure C of IEEE Standard C57.91-1995 [86]. The constant 383 corresponds to 110°C reference temperature (for normal life expectancy [86]). The constant 1500 is the empirical constant obtained from various experimental results conducted on oil cooled

transformers and is described in Section I.2 of IEEE Standard C57.91-1995 [86]. While calculating the energy available, the LOL is calculated for every sample and the average of the calculated LOL is verified in order to ensure that the added energy is within the limits of the expected value.

Figure 5.4 Flowchart of the algorithm used for determining the power limits

5.4.1 P^{limit} Estimation based on Transformer LOL Calculation

The LOL for the transformer is calculated for every day using the load data obtained from Section 5.4.2.1, which is considered as the base LOL. The P^{limit} is calculated for 1% additional LOL with only overnight charging at time between 22:00 hours and 06:30 hours. The results are shown in Table 5-6.

Table 5-6 P^{limit} with 1% additional LOL

Year 1	220kW
Year 2	227kW
Year 3	235kW
Year 4	237kW
Year 5	238kW

The above calculations are carried out without considering the changes in ambient temperature. The impact of ambient temperature is critical in many regions. Hence, to include the impact of the changes in ambient temperature across different seasons, the calculation is repeated using actual temperature in calculation of Θ_H . Since the temperature data used is based on one minute interval, (5.12) is used for temperature approximation also. It is to be noted that half-hourly temperature data for the corresponding years used in Section 5.2.1.1 are not available. Hence, the temperature data of years 2010 and 2011 are used for generating the stochastic samples of temperature.

The new P^{limit} is calculated for same 1% additional LOL with only overnight charging at time between 22:00 hours and 06:30 hours (same as Table 5-6). The results are shown in Table 5-7. It can be observed that there is significant increase in the value of P^{limit} in all cases. Even though the difference in mean temperature during different months does not change much in Singapore, there is significant increase the in value of P^{limit} . This phenomenon is due to the charging period, i.e., overnight charging between 22:00 hours and 06:30 hours. The histogram of the average temperature during the charging period is shown in Figure 5.5 for the year 2011. Due to the cooler temperature (in comparison with the considered ambient temperature of 30⁰ C) during the night hours, the %LOL is lesser, hence more energy can be supplied by the transformer for same limitations of 1%

Table 5-7 New P^{limit} after considering changes in ambient temperature

Year 1	233kW
Year 2	239kW
Year 3	247kW
Year 4	251kW
Year 5	250kW

additional LOL. A vice versa phenomenon could be observed if the analysis is carried out for day time charging.

Figure 5.5 Histogram of average temperature during the charging period

5.5 Summary

A methodology for estimating the optimal number of EVs that can be deployed under a smart grid was proposed in this chapter. Stochastic samples and Monte-Carlo simulations were used for estimating the spare energy available. The proposed method was applied to a typical case study and the expected spare energy available was calculated by varying the power limits during the charging period. The estimation was performed for a period of five years and the results were tabulated. The optimized number of EVs was determined for average expected spare energy of 5 years. The constraints for optimization were also varied and the corresponding results were listed. The proposed method was validated using scheduling process and load models of EVs. The chargeability of the EVs to the desired SOC was verified for a period of 5 years in the validation process. Stochastic samples were used for determining the energy required for each vehicle on any given day. The results showed that the method is highly accurate as in most of the scenarios the EVs were charged to the desired SOC. A cost-benefit analysis was also discussed for one particular case. The cost-benefit analysis showed that it takes approximately 6 years for recovering the investment cost of the charging stations with current parity prices for different categories of vehicles. The time to recover the

investments is dependent on a set of criteria and by fine-tuning the criteria, the time to recover the investments can be reduced. This flexibility will improve the business prospects of setting up the infrastructure required for using EVs in Singapore. Another important perspective of this spare energy availability mechanism is its inherent uncertainty. This has been examined by using Monte Carlo simulations which account for the uncertainty and variability in the EV load and load demand of any particular building. The ease of extending this methodology for any type of scenario allows for replication at the national level in Singapore and beyond. A method for determining the power limits required for EV scheduling based on transformer's loss of life was also presented.

CHAPTER 6 CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

6.1 Conclusions

In the near future, more and more utilities and governments around the world will be actively involved in incorporating intelligence to their traditional electricity generation, transmission and distribution systems. This will pave a way for a smart grid system that offers a completely automated electricity monitoring and control system which intelligently integrates the actions of utilities and consumers to efficiently generate, deliver, and use electricity. Market penetration of EVs has the possibility to continue to gaining momentum, as is the move towards increasingly distributed, clean and renewable energy sources. EV charging shifts a significant portion of transportation energy to the building electricity meters. The communication infrastructure provides the necessary communication and control functions needed to implement critical energy management services while integrating EVs such as charging management, demand side management and other auxiliary function management such as V2G.

In this thesis, a dynamic priority based real-time scheduling algorithm was proposed in [44]. The dynamic scheduling algorithm proposed in this research used a data-driven model based approach to overcome the disadvantages of existing scheduling methods. The algorithm was proposed for time coordinated charging and further extended to power coordinated charging in [45]. Appropriate choice of priority criteria is essential for robust performance of the EV scheduling algorithm. Furthermore, the customer's satisfaction achieved using traditional and modified robust dynamic scheduling algorithms [40]-[43] can be enhanced using proper combination of priority criteria. Hence in this research, analysis on the impact of each priority criterion as well as the impact of various combinations of different priority criteria on the chargeability of the EVs to the required SOC and fairness in the allocation of charging time was carried out. The need for using weighted priority criteria for scheduling EV charging was also evaluated and the impact of using optimal weights required for different cases was also presented. The analysis can serve as a guideline while selecting different parameters as priority criteria for any scheduling algorithm. A new approach for determining the load demand of EVs based

on previous charging profiles was introduced [46]. The aging process of the battery, which depends on the equivalent number of charging cycles the battery has undergone can be captured easily with the proposed method. As the proposed method is completely data-driven, it can be employed seamlessly in current and future urban environments without any significant modifications to the existing systems. Furthermore, once a group EVs is deployed, increasing the number of EVs integrated to the system and accounting for the changes in power consumption of EVs deployed is relatively simple.

The estimation of real-time V2G capacity of EVs is crucial for using EVs as distributed energy storage. A novel algorithm for half-hourly V2G capacity estimation using real-time dynamic EV scheduling was proposed [44]. The proposed V2G estimation method was also compared with the fixed minimum SOC limited estimation method and plug-in probability based estimation methods which do not employ scheduling of EVs. It is observed that the proposed method can improve the accuracy of V2G estimation and was not affected by the time remaining before departure. An intelligent preemptive demand response management (DRM) using dynamic EV charge scheduling was proposed [47]. The proposed method is applicable for buildings where multiple EVs are charged in groups. The proposed method also considers the chargeability of the EVs to their desired SOC's using the proposed dynamic charge scheduling algorithm so as to ensure that the EVs can be considered as an interruptible load. The dynamic priority based on appropriate priority criteria is used for DRM of EVs. The proposed methods are highly suitable for high-rise buildings, hence can be directly applied in cities such as Singapore. In addition, the proposed methods are highly flexible and scalable with little modifications. Hence, it will be easy for the building operators to utilize the auxiliary functions of EVs to improve the energy efficiency of the buildings.

A methodology was proposed for the estimation of the optimal number of EVs that can be deployed under a given smart grid. Monte-carlo simulations and linear programming were used for the estimation [48]. The methodology was applied to calculate the optimal number of EVs that can be deployed under a high-rise building in Singapore. The method was validated using load demand data of 5 years, data-driven load model of EVs and EV load scheduling. The cost-benefit analysis for the installation of charging stations in buildings was also discussed by varying different parameters. The limits required for EV scheduling can be obtained using the methodology proposed for estimating additional

power that a distribution transformer can supply for the integration of EVs with a predefined additional loss of life [49]. The methodology proposed and the cost benefit analysis carried out would be a reference for building operators who would like to deploy EV charging stations, which in turn will have an influence on number of commuters accepting EVs.

6.2 Recommendations for Future Research

The followings are some recommendations and issues opened for future research and development:

1. The proposed priority based load shedding and scheduling could be extended to other equipment with large time constant such as air conditioners and refrigerators. For example, the integration of solar PVs into the distribution network creates various stability and reliability issues associated with the intermittency of solar PV power generation. Energy storage is a vital component required for overcoming the intermittency of solar PVs. A novel DRM based on the priority based load shedding and scheduling for loads with large time constants could be employed so as to create virtual energy storage. The virtual energy storage thus created could be used for leveling the intermittent output of solar PVs. The virtual energy storage concept is based on the approach of reducing the non-critical load demand when there is a power deficit and increasing the load demand when there is a power surplus. Furthermore, it is similar to the virtual power plant concept. The DRM algorithm involves controlling loads with large time constants such as air conditioning systems based on the forecasted solar PV generation. The algorithm is highly suitable for megacities which have high number of multi-storey residential buildings and commercial/office buildings. Utilizing the virtual storage capacity available from the devices will reduce the investment as well as the operation cost of renewable energy such as solar PVs.
2. One of the major ancillary services that EVs can provide is its function as smart energy storage (SES). With EVs considered as SES, it is ideal energy storage for solar PV system installed in commercial/office facilities. This is due to the fact

that the idle time period of the EVs during the day time, and the time period during when the solar PV requires the energy storage intersect perfectly. The idle time period of the EVs is the period when the EVs are immobile and connected to the building for charging. However, it should be demonstrated that using EVs as SES for solar PV system in commercial/office facilities does not have huge impact on the drivability and the life time of EVs. To get a clear picture of the expected loss of life for the EV batteries, the depth-of-discharge (DoD) analysis is required for such a system where EVs are used as SES for solar PV. Furthermore, the DoD of the individual EV batteries depend on the priority criteria used for discharging the particular EV battery. A comparison of DoD of all the EVs while using different priority criteria should be studied and verified using experimental results in a laboratory scale setup.

3. Experimental verification of the ANN based load model proposed in Chapter 3 using the charging profiles of Lead-acid and Lithium-ion batteries is required for adding significance to the proposed method. The charging profiles of the batteries should be collected over their life time. The charging profiles should be then used for analyzing and verifying that the proposed ANN model could predict the changes in power consumption and energy consumption. The changes in power consumption and energy consumption are due to the aging process of batteries and other components used for charging. Furthermore, the information obtained from the proposed ANN model could be used to update the parameters of batteries used in other models also.

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1. **K. Nandha Kumar**, B. Sivaneasan, P. H. Cheah, P. L. So, and D. Z. W. Wang, "V2G capacity estimation using dynamic EV scheduling," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 1051-1060, Mar. 2014. (*Impact Factor: 4.334, Google Scholar Citation Count: 18*)
2. B. Sivaneasan, **K. Nandha Kumar**, K. T. Tan, and P. L. So, "Preemptive demand response for buildings," *IEEE Trans. Sustainable Energy*, vol. 6, no. 2, pp. 346-356, Apr. 2015. (*Impact Factor: 3.842, Google Scholar Citation Count: 1*)
3. **K. Nandha Kumar**, B. Sivaneasan, and P. L. So, "Impact of priority criteria on electric vehicle charge scheduling," *IEEE Trans. Transportation Electrification*, vol. 1, no. 3, pp. 200-210, Oct. 2015.

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2. **K. Nandha Kumar**, P. H. Cheah, B. Sivaneasan, P. L. So, and D. Z. W. Wang, "Electric vehicle charging profile prediction for efficient energy management in buildings," in *Proc. 10th International Power and Energy Conference (IPEC)*, Vietnam, Dec. 2012. (*Google Scholar Citation Count: 6*)
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K. Nandha Kumar, B. Sivaneasan, K. T. Tan, J. S. Ren, and P. L. So. Electric Vehicles as Energy Storage: V2G capacity estimation. In *Energy Storage for Smart Grids: Planning and Operation for Renewable and Variable Energy Resources (VERs)*, Elsevier, Oct. 2014.

APPENDIX A

LOAD MODEL USED IN DRM

The DRM program proposed considers the EVs, air conditioner (AC) system's variable speed drives (VSDs) and Interruptible loads (ILs) as the loads that participate in the demand response. Load models are developed to allow the analysis on the capability of the proposed DRM program to reduce the building's overall power demand.

EV load model

The power demand of one EV charging is based on the estimated charging demand of the EV and the charging station circuit breaker ON/OFF status, and is given by

$$P_{EV,i} = P_{CS,i} \cdot x_{i,j} \quad (\text{A.1})$$

where i is the EV number and $x_{i,j} = \{0,1\}$ represents the circuit breaker "OFF" and "ON" status of the EV charging station for one particular half-hour interval j . $P_{CS,i}$ is the estimated charging power demand of the i^{th} EV in the next interval. It is obtained by using the current SOC of the EV, time period of the next interval and the predicted charging profile of the EV. Data mapping with current SOC as the identification parameter is used to determine the starting point in the predicted charging profile. The number of data points equal to the number of minutes in the next interval (30 minutes in this case) is extracted to calculate the value of $P_{CS,i}$. The load model for predicting the charging profile of the EV using initial SOC, final SOC and previous charging profile is described in [21]. The total building's EV power demand is then given by

$$P_{EV,total} = \sum_{i=1}^n P_{EV,i} \quad (\text{A.2})$$

where n is the total number of EV charging stations installed in the building.

AC system load model

The power demand of one AC system load is based on its motor power rating, circuit breaker ON/OFF status and motor operating speed in relation to the VSD frequency as follows:

$$P_{AC,k} = P_{ACmotor,k} \times B_{ACmotor,k} \times \frac{f_{VSD,k}}{f_s} \quad (A.3)$$

where k is the AC system unit number, $P_{AC,k}$ is the AC system power demand of the k^{th} unit, $P_{ACmotor,k}$ is the AC system motor rated power of the k^{th} unit, $B_{ACmotor,k}$ represents the circuit breaker ON/OFF status of the k^{th} unit, $f_{VSD,k}$ is the VSD operating frequency and f_s is the supply frequency. The total building's AC system power demand is then obtained by

$$P_{AC,total} = \sum_{k=1}^r P_{AC,k} \quad (A.4)$$

where r is the total number of AC system loads installed in the building.

IL model

The power demand of other ILs is based on the load rated power and the Load Control Module (LCM) ON/OFF status as represented by

$$P_{IL,\ell} = P_{ILrated,\ell} \times LCM_{IL,\ell} \quad (A.5)$$

where ℓ is the IL unit number, $P_{IL,\ell}$ is the IL power demand of the ℓ^{th} unit, $P_{ILrated,\ell}$ is the IL rated power of the ℓ^{th} unit and $LCM_{IL,\ell}$ represents the LCM ON/OFF status of the ℓ^{th} unit. The total building's IL power demand takes the form of

$$P_{IL,total} = \sum_{l=1}^w P_{IL,\ell} \quad (A.6)$$

where w is the total number of ILs in the building.

The building current load demand P_{CD} can then be obtained by the summation of the total EV, AC system and IL power demands. The building current load demand is given by

$$P_{CD} = P_{EV, total} + P_{AC, total} + P_{IL, total} + P_{others} \quad (A.7)$$

P_{others} is the power demand of other essential and non-essential loads that do not participate in the DRM program. P_{others} is used as the control variable in the DRM analysis to increase P_{CD} to $x\%$ and $y\%$ of CC/DL.