

Optimization and Integration of Electric Vehicle Charging System in Coupled Transportation and Distribution Networks

Yijia Wang

B.E.

A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

School of Electrical and Information Engineering

Faculty of Engineering and Information Technologies

The University of Sydney

2019

Declaration

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Abstract

With the development of the EV market, the demand for charging facilities is growing rapidly. The rapid increase in Electric Vehicle and different market factors bring challenges to the prediction of the penetration rate of EV number. The estimates of the uptake rate of EVs for light passenger use vary widely with some scenarios gradual and others aggressive. And there have been many effects on EV penetration rate from incentives, tax breaks, and market price.

Given this background, this research is devoted to addressing a stochastic joint planning framework for both EV charging system and distribution network where the EV behaviours in both transportation network and electrical system are considered. And the planning issue is formulated as a multi-objective model with both the capital investment cost and service convenience optimized. The optimal planning of EV charging system in the urban area is the target geographical planning area in this work where the service radius and driving distance is relatively limited. Compared with existing papers, the major contributions of this work can be summarized as below:

A flexible planning model is proposed in Chapter 4, in which the uncertainty of the penetration rate of EVs is incorporated. The Monte-Carlo simulation method is used to evaluate this uncertainty. And a confidence interval is employed to enable the efficiency and effectiveness of this uncertainty analysis.

In Chapter 4, a dynamic traffic assignment model is incorporated with a flow-capturing location model to evaluate the captured traffic flow based on the optimal planning result. This method can best model the driving behaviours of EVs in urban areas. With the queuing theory and waiting time incorporated, the simulation result indicates a concept planning scheme with the best commercial value, social warfare and service capability.

In Chapter 4 and Chapter 5, the probabilistic battery SOC distribution for on-route EVs is analysed to evaluate the EV arrival rate of FCS in the transportation network. This model assumes that drivers are more likely to approach FCS for fast charging if the battery SOC of the EVs is low. And we use the sigmoid fitting curve in this work to compute the rate of EV approaching the FCS for charging service.

Chapter 5 propose the joint planning and coordinated operation strategy of distributed generation and the EV charging system in the power network. In this work, a multi-objective optimization model is formulated. The captured traffic flow was used as an indicator to optimize the location of FCS in this thesis. The power fluctuation, increased load and system stability issues from both the large integration of intermittent PV and future penetration of EVs are considered together.

An Energy Management System of Smart Building with Electric Vehicle, Photovoltaic and Battery Energy Storage is proposed in Chapter 7 to discuss the charging behaviour of parking Electric-Vehicle.

Thesis Authorship Attribution Statement

Chapter 4 of this thesis will be published as Y. J. Wang, Y. Xu, Z. Y. Dong, D. J. Hill, "A Stochastic Joint-Planning Framework for Electric-Vehicle Charging System and Distribution Network in Urban Area". I coauthored the study in S. Wang et al., "A stochastic collaborative planning approach for electric vehicle charging stations and power distribution system," in Proc. IEEE Power Energy Soc. General Meeting, Boston, MA, 2016, pp. 1–5.

Chapter 5 of this thesis will be published as Y. J. Wang, Y. Xu, Z. Y. Dong, D. J. Hill, "Joint Planning of EV Charging System and Renewable Generation in Urban Distribution Network".

Chapter 6 of this thesis is published as Y. J. Wang, Y. Xu, Z. Y. Dong, W. Zhang, "Multi-stage planning and economic analysis of intelligent Energy Management System in a Smart Building", Proc. 2015 the International Conference on Power System Control, Operations and Management (APSCOM), Hong Kong, Jul. 2015.

The following papers are also published as authorship or co-authorship:

W. Zhang, Yan Xu, Zhao Yang Dong, Yijia Wang, and Rui Zhang. An efficient approach for robust scopf considering load and renewable power uncertainties. In 2016 Power Systems Computation Conference (PSCC), pages 1–7, June 2016.

Y. J. Wang, Z. Y. Dong, Y. Xu, J. Ma, Y. Zheng, "Enabling large-scale energy storage and renewable energy grid connectivity: A power-to-gas approach", July 2015, Zhongguo Dianji Gongcheng Xuebao/Proceedings of the Chinese Society of Electrical Engineering 35(14):3586-3595

In addition to the statements above, in cases where I am not the corresponding author of a published item, permission to include the published material has been granted by the corresponding author.

Acknowledgment

I would like to thank to my supervisors Prof. Zhao Yang Dong, Prof. Jin Ma and Dr. Yan Xu for their consistent help and support throughout my research. I would also like to express my appreciation to Prof. David John Hill for giving me the opportunity to work with him.

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Nomenclature for Abbreviation

EV	Electric Vehicle		
CEM	Clean Energy Ministerial		
FCS	Fast Charging Stations		
BSS	Battery Swap Stations		
DG	Distributed Generation		
DS	Distribution System		
PEV	Plug-in EV		
PHEV	Plug-in Hybrid EV		
BEV	Battery Electric Vehicle		
FCLM	Flow Capturing Location Model		
FRLM	Flow-Refuelling Location Model		
V2G	vehicle-to-grid		
GSI	Gravity Spatial Interaction Model		
OD	Origin-destination		
UETAM	User Equilibrium based Traffic Assignment Model		
BPR	Bureau Public Roads		
MCLM	Maximal Covering Location Model		
FCLM	Flow Capturing Location Model		
CFRLM	Capacitated Flow-refuelling Location Model		
FRLM	Flow Recharging Location Model		
PDF	Probability Density Function		
MOEA/D	Multi-objective evolution algorithm		

Symbolic

$\alpha_{\scriptscriptstyle m}^{\scriptscriptstyle CP}$	Binary decision variable for the building of CP at node n .
α_n^{FCS}	Binary decision variable for the construction of Fast Charging Station at transport site <i>n</i>
$\alpha^{^{time}}$	Negative scaling parameter for travel time
$eta^{\scriptscriptstyle FCS}$	Positive scaling parameter for the availability of FCS
$eta_i^{\scriptscriptstyle DG}$	Binary decision variable for the construction of DG at distribution node i
$\delta^{rs}_{\scriptscriptstyle m,q}$	Binary variable denotes whether the transportation link m exists on the path n
$\delta^{\scriptscriptstyle FCS}_{\scriptscriptstyle n,q}$	Binary variable indicates whether the FCS site n exists on path q
$\delta_{\scriptscriptstyle n,qd}^{\scriptscriptstyle FCS}$	Binary indicator variable denote whether the deviated traffic flow on path qd from original path q can be captured by the FCS at transport site n
$ heta_{ij,t}$	Phase angle deviation of branch ij at time step t
$\lambda_{n,t}$	Mean EV arrival rate of FCS at node n in time step t
$\lambda_{i,t}$	The number of EVs that can be served by FCS located at node i in time t
μ	Parameter of exponential distribution for mean service rate of charging facilities
$\mu_{\scriptscriptstyle R}$	average driving distance
$ ho_{n,t}$	The occupation rate of FCS at node n in time step t
$\sigma_{\scriptscriptstyle R}$	Standard deviation of past driving range normal probability density function
$ au_q^{rs}$	Binary variable that denote whether the traffic flow on path n can be captured
ϕ^{a}	Set of the distribution line types
ϕ^{S1}	Set of candidate nodes of existing substations for reinforcement
$\pmb{\phi}^{b}$	Set of substation capacity types for reinforcement
ϕ^{s_2}	Set of candidate nodes for substation construction
ϕ^{c}	Set of substation capacity types for construction

$\phi^{^{DL}}$	Set of existing and candidate distribution lines
ϕ^{FCS}	Set of candidate site for Fast Charging Station Construction
$\phi_q^{\scriptscriptstyle FCS}$	Set of candidate FCS that could capture the traffic flow on path q
$\phi^{\scriptscriptstyle OD}$	Set of all possible OD pair <i>rs</i> in transportation network
A^{T}	Set of transportation system links
$A^{q,m}$	Set of arcs of path q in terms of EV_m
A^q	Set of arcs of path q
c_m^T	The traffic flow capacity of link <i>m</i>
c_a^{DL}	Construction cost of type <i>a</i> distribution feeder
c_b^{S1}	Reinforcement cost of substation with capacity type b
c_{c}^{S2}	Construction cost of substation with capacity type c
c^{FCS}	Capital cost of fast charging facility
C_n^{Land}	Land utilization cost for FCS (related to the geographical location)
C ^{FCSOther}	Other capital cost for FCS
c^E	Price of unit electricity
c^{DG}	Capital cost of distributed generation facilities
$c^{DGOther}$	Other investment cost for distributed generation construction
C_i^{FCS}	The cost for FCS construction at node <i>i</i>
d^{DL}, d^{S}	Capital recovery factor for distribution line and substation investment
d^{FCS}	Capital recovery factor for fast charging station investment
d^{DG}	Capital recovery factor for distributed generation investment
d_{rs}^{T}	The distance between the OD pair <i>rs</i> in transportation system
$d^{q,m}(i,j)$	The distance between any two nodes i and j on path q in terms of EV_{m}
$D_{n,t}^{CP}$	The covered CP charging demand at node n in time step t
f_t^{rs}	The travel demand of the origin and destination pair <i>rs</i>
f_q^{rs}	Number of traffic flow on path q connecting OD pair rs

$f_{q,t}^{rs}$	Number of traffic flow on path q connecting OD pair rs at time step t
$f_{m,t}^T$	Number of traffic flow on link m at time step t
$g_{ij,a}$	Conductance of feeder ij with type a
${\mathcal S}_q^{char}$	Fraction of EVs served by FCS on pre-determined path q
$g_{\scriptscriptstyle qd}^{\scriptscriptstyle dev}$	Fraction of EVs flow on path $_{q}$ will transfer to the deviation path dev
k_i^{DG}	Size of the candidate DG at distribution node <i>i</i>
l_{ij}	Length of distribution line <i>ij</i>
N^{T}	Set of transportation system nodes
N^q	Set of nodes of path q including source and sink nodes
$N^{q,m}$	Set of nodes of path $_{oldsymbol{q}}$ in terms of $\mathit{EV}_{_m}$ including source and sink nodes
$P_{n,t}^0$ service	Probability of a charging facility of FCS at node n in time step t is under charging
$P_{i,t}^{CP}$	Nodal charging power of CP at DS node i in time t
$P_{n,t}^{FCS}$	Charging power of FCS at transportation network node n in time t
$P_{i,t}^{DG}$	Active power generated from DG at node i in time t
$P_i^{DG\min}$	Power generation limit of DG at node <i>i</i>
q	Index of paths of the transportation network
Q	Set of all the candidate paths in the transportation network
Q_i	Set of all the paths in the transportation network that travel through node <i>i</i>
Q_{rs}	Set of paths connecting the origin and destination pair rs
R_O^{EV}	Actual past driving distance before the journey on route q
R_D^{EV}	Available driving distance after the journey on route q
\mathbf{S}_{n}^{CP}	The determined size of CP which indicate the number of charging facilities at node n
$\overline{S_i^0}$	Apparent power capacity of the existing substation at node <i>i</i>
$\overline{S_{i,b}^{S1}}$	Apparent power capacity of the type b reinforced substation at node $_i$

$\overline{S_{i,c}^{S2}}$	Apparent power capacity of the type c constructed substation at node i
t	Time Step
t_m^0	The free flow travel time on link <i>m</i>
$t_{m,t}^T$	Travel time at link m at time step t
$t_{q,t}^{rs}$	Travel time if selecting the path q at time step t
Т	Set of time intervals $T = \{1, 2, \dots 24\}$
Τ'	Set of time intervals with virtual time step t, $T = \{1, 2, \dots 24, t'\}$
$U_{i,t}U_{j,t}$	Voltage magnitude of bus i and j at time step t
$U_i^{\min} \ U_i^{\max}$	Voltage limit at DS node <i>i</i>
$W_r^T W_s^T$ gravitation	The weight of nodes in transportation system - represent the Traffic flow
W_n^{RH}	Average time a customer spends in waiting line for waiting service.
x_{ij}^q	The arc flow variable for <i>arc</i> (<i>ij</i>)
χ^{q,EV_m}_{ij}	The arc flow variable for $arc(ij)$ on path q in terms of EV_m
$X_{ij,a}$	Binary decision variable for building type a distribution feeder on link ij
$\mathcal{Y}_{i,b}^{S1}$	Binary decision variable for reinforcing the substation at node $\scriptstyle i$ with type $\it b$
$y_{i,c}^{S2}$	Binary decision variable for constructing the substation at node $_i$ with type c
Z_n	The number of charging facilities in Fast Charging Station at node n
Z_n^{FCS}	Size of the candidate FCS at transport site n
$z^{\min} z^{\max}$	Size limit of Fast Charging Station
<i>i</i> , <i>j</i>	Distribution nodes
m, n	Index of nodes for the transportation network
O, D	Enter and exit node of transportation system
r^q, s^q	Source node and sink node of path q
r_m, s_m	Source node and sink node of $\mathit{EV}_{\!\scriptscriptstyle m}$ on path $_{{m q}}$

G_{ij} , B_{ij}	Real and imaginary part of the nodal admittance matrix
$P_{i,t}^S Q_{i,t}^S$	Active and reactive power from substation at DS node i in time t
$P_{i,t}^L Q_{i,t}^L$	Active and reactive power demand at DS node i in time t
$P_{ij,a,t} Q_{ij,a,t}$	Active and reactive power flow of type a distribution line ij in time t
$g_{ij,a}$ $b_{ij,a}$	Conductance and susceptance of type a distribution line ij
$AW_{n,t}$	Average waiting time of FCS at node n in time step t
<i>Cap</i> _i	The capacity of the FCS located at node <i>i</i>
$CD_{i,t}$	The number of EVs with charging demand at FCS located at node i in time t
$ord^{q}(i)$	The ordering index of node i on path q
SoC_{O}^{EV}	Initial SoC at the entering point of transportation network
SoC_D^{EV}	Available SoC at the exit point of transportation network

Chapter 1 Introduction

Fossil fuels are the dominate energy source for both the electricity generation and transportation industry. However, in recent years, the climate change has aroused global awareness about the negative impacts of using fossil fuel. Governments and industries are moving toward the use of clean energy sources and reducing environment pollution. In this case, it is most likely involved an extensive use of Electric Vehicle (EV) for transportation electrification and adopting renewable energy sources for electricity generation. As a cleaner method of transportation with less carbon emission and energy consumption, electric vehicle is regarded as a feasible option for replacing petroleum-fuelled vehicles. With the development of power electronics and battery technology, millions EV will be employed in transportation and integrated into the electric system. However, lack of sufficient charging infrastructure is a critical barrier to successful deployment of EVs at this large scale. And the intensive use of EV and DG introduces several challenges in distribution network. Therefore, there is an increasing need today to build a properly planned infrastructure for EV charging and develop novel planning methods of active distribution network.

1.1 Electric Vehicle

Advances in battery technology, evolved vehicle industry, electric grid automation and other driving factors are increasing the penetration rate of EVs and promoting the long-term shift to more efficient transportation. For example, the cost of battery storage, which account for up to 25% of the cost of EV, are predicted to fall from above \$1,000 per kWh in 2007 to \$200 in 2020 [1]. In the last five years, the number of electric vehicles has increased significantly and can now be found on roads throughout the world. New registrations of EVs increased by 70% between 2014 and 2015. And it is expected to have a large share in the future transportation system over the next 20 years. The Electric Vehicle Initiative (EVI) is a multi-government policy forum established in 2009 under the Clean Energy Ministerial (CEM), dedicated to accelerating the deployment of EVs worldwide with the goal of a global deployment of 20 million electric cars by 2020 [2-3]. Furthermore, the Electric Power Research Institute reports that 62% of U.S. fleet vehicles will be replaced by PEVs by 2050 [4].

EVs use electric motors powered by electrical energy stored in the battery for driving. This powering model consumes less energy, produces comparatively little emission and gives a feasible option for replacing petroleum-fuelled vehicles. EVs are available in a variety models with varying types, ranges and capabilities. Generally, the EV consumption rate is 170-230 Wh/km. EVs are divided into two basic types: Plug-in Hybrid EV (PHEV) and Battery EV (BEV) and are compared in the table 1-1. And the EV sales, market share, and BEV and PHEV sales share in selected countries are summarized in figure 1-1 [4].

	Plug-In Hybrid EVs		Battery EVs	
Motor	Two Motors: Internal combustion engine and electric motor		One or more electric motors	
Battery Capacity	Medium-capacity battery		High-capacity battery	
Range	All-electric 20 to 70 km		100 to 400 km	
	Model	Range	Model	All Electric Range
	Chevrolet Volt	53 mi (18 kWh)	Nissan Leaf	150 mi (40 kWh)
	Mitsubishi Outlander	37 mi	Chevrolet Bolt	238 mi (60 kWh)
	Toyota Prius	25 mi (8.8 kWh)	Tesla Model S	234/360 mi (60/90 kWh)
	Cadillac CT6	31 mi (18 kWh)	Tesla Model X	238/257/289 mi (100 kWh)
	Hyundai loniq/Sonata	27 mi (8.9/10 kWh)	Tesla Model 3	220 mi
	Audi A3 E-Tron	16 mi (9kWh)	Hyundai loniq E	124 mi
Models and All	Ford Fusion/C-Max Energi	20 mi (7/8 kWh)	Kia Soul EV	93 mi (27 kWh)
Lieutio hange	Kia Optima	29 mi (10 kWh)	Smart Fortwo	70-80 mi(17kWh)
	Mercedes C350/S550/GLE550e	20/20/12 mi (6/8/9 kWh)	Mitsubishi i-MiEV	63 mi (16 kWh)
	Mini Cooper S E	25 mi (8 kWh)	Ford Focus Electric	115 mi (23 kWh)
	Porsche Cayenne S	14 mi (10.8 kWh)	FIAT 500e	84 mi (24 kWh)
	Volvo XC60/XC90	20/14mi(10/9kWh)	BMW i3	114 mi (33 kWh)
	BMW 330e/530e/740e xDrive/i8/X5 xdrive40e	14/31/14/25/13 mi (7/9/9/7/9 kWh)	Mercedes B-Class	85-100 mi (28-31.5 kWh)
	Honda Clarity	42 mi (17 kWh)	Honda Clarity E	89 mi (25 kWh)
			Volkswagen E-Golf	125 mi (36 kWh)

TABLE 1-1Comparison of EVs [4]

EVs are still not as competitive as conventional vehicles. The constraints of EV include relatively short driving range, limited available charging facilities and longer battery recharge times. All those factors in combination with consumers' unfamiliarity with EV prevent the wide deployment of EV. The gasoline-powered vehicle can travel 500km or more, which is significantly better than the EV's performance. The EVs in the market can only travel 100-160 km on a single charge. And it takes hours to recharge EV using the charging post systems. Additionally, the public also criticize the inadequate public charging facilities which cause a lot of inconveniences in using EV. The large capital investment cost and future uncertainties bring challenges for investors or grid operators to make decision on charging facility investment. However, it is expected that the technology advancement in battery energy storage and power electronics can contribute to EV development and the promotion of EV could also benefit from the increasing demand of EV to facilitate power system operation.



Fig. 1.1 Electric car sales, market share, and BEV and PHEV sales shares in selected countries, 2010-16 [4]

1.2 Electric Vehicle Charging Facility

EVs are generally plugged into a source of electrical power to recharge. The number of available EV models and the number of EVs on the street are growing rapidly, as is the need for charging stations. Although the current availability of public charging station is limited, publicly and privately funded project in charging station construction is increasing rapidly. New charging technologies, government policy and market tariffs are accelerating the deployment of public stations. According to a new EV Charging Infrastructure Report by HIS Inc., the global EV Charger market is forecast to grow from more than 1 million units in 2014 to more than 12.7 million units in 2020 [5].

1.2.1 Electric Vehicle Charging Facility

EV charging methods can be summarized into two types: destination charging and on-route charging. Destination charging includes home charging, workplace charging and parking lots charging etc. Destination charging needs are generally satisfied by distributed charging spots in private or public charging posts. On-route charging demand are mostly satisfied by fast charging stations (FCS) and battery swap stations (BSS). The destination charging is the primary charging method for EVs since most of people's daily mileages are below the driving range pf EVs in the market. However, the fast charging station and battery swap station is still an important complementary charging facility in case of increasing flexibility of driving experience and long-distance driving demand.

Generally, the EV charging facilities are divided into three types based on the nature of service and charging power: Level 1, Level 2 and DC fast charging. Different types of charging facilities have different service modes, target customers and technical parameters which initiate different charging power demand and charging behaviours of EVs. The characters of different charging facilities are compared in table 1-2.

For the BSS, EV use batteries by leasing from relative service. This operation mode can experience various advantages. First, battery can be replaced in a short time and EV drivers could resume their journey in minutes with a full-capacity battery. Second, the charging of batteries is centralized and controllable. And this mode can reduce the impact on power system from EV charging to the best extent. Third, the EV batteries can be charged in slow-charging mode which can extend the battery life cycle. Forth, the large number of battery packs in BSS can be used for grid-support.

For different type of charging facilities, the planning concerns are different. For level 1 and level 2 charging spots, only the size is considered in the planning framework, as the location is the existing or predetermined parking lots. For FCS and BSS, both the location and size should be decided in planning.

	Level 1	Level 2		Fast Charging Station			
Voltage	120V AC	240V AC		AC 3-ph	480V DC		
Power	< 3.7 kW	>3.7 &	≤ 22 Kw	> 22 &	< 200 kW	< 150 kW	
		\leq 22 kW		\leq 43.5 kW			
Charge Duration	6-10 hrs	1-3 hrs		<20 mins			
Range	4-6 mi/hr	20-60 miles/hour		60-80 miles in 20 mins			
Location	Households	Residential/Commercial/		Roadside			
		Industrial Parking Lots					
Planning	-	Sizing		Siting and Sizing			
Advantages	Low installation cost;	More energy and time		Reduced charge time			
	Low impact on	efficient the Level 1;					
	electric utility;	Variety of manufactures;					
Disadvantages	Charging is slow	Higher installation cost;		High installation cost			
		Potentially higher impact		Potentially increased peak			
		on electric Utility;		demand of electric grid			

TABLE 1-2 Ov	erview of EV	' Charging	Facilities
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Туре	China	-	GB/T 20234 AC	Tesla Connector	-	GB/T 20234 DC	Tesla and CHAdeMo
	Europe	-	IEC 62196 Type 2		IEC 62196 Type 2	CCS Combo 2 (IEC 62196 Type2&DC	
	Japan	-	SAE J1772 Type 1		-	CHAdeMO	
	USA	SAE J1772 Type 1	SAE J1772 Type 1		SAE J3068	CCS Combo 1 (SAE J1772 Type1&DC	

There are many benefits to install or operate a charging facility/station, which depends on the type of facility and the location. Charging facility owner could generate revenue directly by providing charging and parking services. The costs of installing and operating a charging station include facilities, land, installation, maintenance, operation and electricity costs. The cost can be reduced by taking advantage of policy incentives. And manufactures are working to decrease these costs substantially as charging equipment volumes increase. Capital cost of charging facilities vary in the types of features offered. The price for Level 2 charging facility is approximately \$1,000 to \$5,000. Fast charging products cost typically \$20,000 to \$50,000 including additional hardware requirements associated with the high-power operation. The installation costs for EV charging facility vary considerably. One estimate is \$15,000 to \$18,000 for a Level 2 station including equipment and installation costs. For a FCS with one DC fast charging unit, the estimate is \$45,000 to \$100,000. The maintenance requirements, in general, includes periodic inspection, testing, and preventive maintenance by a gualified electrical contractor. The estimated annual maintenance costs range from \$25 to \$50 per unit. Electricity costs will depend on the type of charging station installed and the time of EV charging service. The charging service may be required at off-peak, shoulder and peak hour and induce different electricity price level. The EV stock and charging facilities are compared in figure 1.2 [3].



Fig 1.2 EV Stock and Publicly Charging Facilities, by country and type, 2016 [3]

1.2.2 Charging Station Operation Mode

This part explores the potential EV charging station owners including the government, the utility company, commercial investor and private owner. The government entities could lead the early development of the EV charging infrastructure and this could benefit their jurisdictions. The utility company could receive direct benefits from providing charging service and the ownership of charging facility could enable them to coordinate the EV charging schedule for grid stability and security purpose. The commercial investors like retail stores and parking lots are suitable to provide level 2 and fast charging service. This charging business could generate revenue directly from providing charging service. Residents install Level 1 or Level 2 charging for overnight charging needs.

1.3 Electric Vehicle Charging System Planning

The inconvenience to get recharged is one of the major barriers for the penetration of EVs, therefore a planning infrastructure for EV charging facilities could promote the transportation electrification. Figure 1.3 and 1.4 show the distribution of EV charging facilities in USA and Australia and figure 1.5 shows the EV charging facility layout in a specific area in New York City [6].

The ideal station is expected to be convenient, highly visible to potential drivers and aligned to the driving target. Therefore, business owners and building owners need to evaluate carefully between the cost, charging demand, profits and grid capacity. Figure 1.6 outlines an industrial process for EV charging station planning.



Fig. 1.3 EV Charging Facilities Distribution in USA [6]



Fig. 1.4 EV Charging Facilities Distribution in Australia [6]



Fig. 1.5 EV Charging Facilities Distribution in City Area of NYC [6]



Fig. 1.6 Industrial Process for EV Charging Station Planning

1.3.1 EV Charging System Planning in Distribution System (DS)

Large-scale integration of EVs would generate large amount of charging demand with uncertainties, which may impose challenges to the current planning and operation methodologies for power system, especially at the distribution level. One of the major concern of large integration of EV in Distribution System is the system stability. EV population is expected to reach a large market size in the next decade. However, achieving such penetration rates requires wide deployment of charging facilities and power for charging demands in peak times while charging PEVs from grid. The effect of the uncontrolled charging is evaluated by different EV utilisation rate in [7] so that a 20% increase in EV penetration rate will cause 35.8% load increases. Therefore, if not reasonable planned, EV charging can easily lead to power network overloading and it can deteriorate the power quality and even endangers the security of supply. The impacts of EV charging on the grid has been well analysed in [8-11]. It has been approved that a significant large amount of extra power and expansion in power generation shall be needed if 5% of the EVs charge simultaneously using fast charging facility. Thus, distribution grid could easily become a bottleneck for EV development. Therefore, the distribution network constraints shall be considered in EV charging system planning and considerations shall be given to planning distribution grid and EV charging system collaboratively.

1.3.2 Electric Vehicle Charging System Planning in Transportation System

Breakthroughs in connectivity among vehicles, the grid, and other infrastructure will allow the transportation system of the future to use dramatically less fossil fuel and significantly cut greenhouse gas emissions. A sustainable transportation future will rely on multiple solutions, including innovative systems connecting vehicles, utilities, renewable energy sources, and buildings. On one hand, the

transportation network is the platform for EV charging system planning and the travelling behaviour and traffic flow will determine the spatial and temporal distribution of charging demand. On the other hand, the penetration of EV will also change the driving behaviour. Therefore, it is necessary to consider the transportation network in EV charging system planning.

1.3.3 Uncertainties in EV Charging System Planning

The integration of EV introduces more uncertainties into the power and transportation network planning and operation. These uncertainties might include the penetration levels of EVs, temporal and spatial distribution of charging demand, and the implementation of different coordinated charging strategies. Firstly, it is hard to give a prediction of the future EV number in a certain area since the penetration rate of EV can be influenced by various factors, such as market, policy and technology. Secondly, the driving behaviour is diverse and accordingly the temporal and spatial distribution characteristics of EV charging demand are hard to predict. Thirdly, the EV charging load can be affected by some specific coordinated charging strategies and these strategies may help with the uncertainty issues. However, the implementation of coordinated charging strategies is still uncertain as it requires the enhancement of many aspects in power system, such as smart charging devices, control devices, communication network and interaction mechanism. Therefore, it is important to integrate the uncertainty in system planning to accommodate different scenarios and enable the flexibility of the planning result.

1.4 Integration of Distributed Generation (DG) in EV Charging System Planning

According to [12], the increasing number of EV can increase penetration rate of renewable energy. As discussed above, the load will increase significantly with the EV number increase and therefor increasing the need for power generation. Thus, extra demands produced by PEVs should be supplied through fossil-fuel-generation plants, which have higher greenhouse gas emission in the environment. During the past decades, DG has gained increasing concerns and is considered as one of the feasible alternatives to reinforce the distribution systems. The installation of DG is beneficial to avoid both distribution line expansion and fossil fuel plant construction. The sites and sizes of DG should be properly planned to achieve the benefits from DG integration, such as loss reduction, peak load shaving, voltage drop control and investment deferral. On one hand, simultaneous optimal planning (placing and sizing) of EV charging system and DG deliver a holistic solution for system planning, which has not been considered in the studies. On the other hand, employing controlled charging of EVs in a charging station integrated to photovoltaic is a possible method to decrease greenhouse gas emission.

Chapter 2 Literature Review

A lot of research efforts have been devoted to the problem of EV charging to minimize the negative influences of the large-scale penetration of EVs and fully explore the potential benefits from EV integration. EV charging system planning has been well investigated from different aspects, such as solution method, distribution network expansion, traffic flow analysis, EV charging market, incorporating DG units, operational planning, time frame of planning horizon, coordinated charging and micro-grids. A through literature review has been undertaken in this chapter to understand existing academic research works and industrial practice.

2.1 EV Charging Station Planning

The planning issue for EV charging infrastructure includes the charging demand modelling, charging impact qualification and optimal allocation of EV charging stations in a certain area. Generally, EV charging considered in the following work include destination charging, such as private, public and workplace parking lot charging, as well as fast charging, such as FCS. Since fast charging stations play an important role in coupling the transportation and distribution networks, the planning issue of FCS should consider not only the distribution power flow, but also the transportation system and EVs' driving behaviour. Therefore, the planning of fast charging stations should take both transportation and electrical constraints into consideration. The research result and methodologies are performed as below.

2.1.1 The planning framework in transportation system

Planning of gasoline stations has been studied for decades and the corresponding allocation methodologies have been adopted and modified for EV charging system planning. An agent-based decision support system is presented in [13] to identify the patterns of residential EV ownership and driving profiles to develop enable strategic deployment of new charging infrastructures. A maximal covering model is developed in [14] to locate a certain number of charging station in a metropolitan area.

The EV charging system planning framework in transportation system can be divided into three categories:

1) Nodal Demand Based Planning [15-18]:

This method scales the charging demand of the target planning area down to some geographical nodes and locates the charging stations to satisfy charging demand. However, this method does not consider the dynamic nature of EVs. In [15], the road information is quantified into data point and then converted into demand clusters by hierarchical clustering analysis. And then a charging station allocation model is formulated to meet the charging demand of these clusters. A maximal covering model is developed in [16-18] to locate a certain number of charging station in a metropolitan area.

2) Traffic simulation-based planning [19-20]:

This method estimates the PEV charging demand based on the simulation of real world and /or realtime comprehensive individual travel survey data. The simulation method takes the real traffic situation and congestion constraints into consideration [19-20]. However, the qualified data can be hard to be obtained and this method can be unnecessary in predictive planning issue.

3) Flow model-based planning [21-27]:

This method considers the mobility nature of EVs and use origin-destination (OD) traffic flow to estimate the charging demands. The flow capturing location model (FCLM) locate stations on the transportation network to maximize the captured traffic flow without considering the driving range constraint of EVs. Flow-refuelling location model (FRLM) consider the driving range of PEV.

2.1.2 The planning framework in distribution system

As a new type of power demand, the planning issue of charging stations in power system has also drawn attention in research. The siting and sizing of charging station shall be allocated reasonably to meet the charging demand and achieve the qualified charging service. Additionally, the optimal planning strategies for distribution systems have been studied by many researchers for a long time. However, the large penetrated EVs raise new challenges to the distribution system planning and inappropriate site and size of charging station may cause problems in distribution system.

2.1.2.1 EV charging system Planning in Electricity Network

This planning method consider the location and capacity of EV charging station in power systems to satisfy the power system economic or security constraints. However, this method cannot meet the large integration of EVs into electric network. As the distribution system capacity considered in this method cannot accommodate future large charging load from increasing utilization of EV. In [28], a two-step screening method was developed to locate charging stations in a distribution network first and then the optimal sizing is determined by a modified primal-dual interior point algorithm. [29] studies electric vehicle charger location problems and analyses the impact of public charging infrastructure deployment on increasing electric miles travelled, thus promoting battery electric vehicle (BEV) market penetration.

2.1.2.2 DS Planning with EV Integration

By far, the issue of DS planning has been explored in many research works. The mathematical formulation and solution algorithms have been systematically investigated in [30-38]. Based on the periods of planning horizon, the distribution planning issue can be formulated as one-stage static planning [30-37] and multi-stage dynamic planning [38].

However, widespread utilization of EV and the corresponding charging demand would challenge the traditional planning strategy of distribution system. By far, some research works have analysed the potential impacts of EVs on distribution system [39-41]. And some literatures focus on the expansion of distribution system with the integration of EVs [42]. According the interactive nature between EV charging system planning and distribution network, the planning framework can be summarized into two different types: two-step planning method and joint planning method. For two-step planning framework, the EV charging system is planned first, and the expansion planning of DS is conduced accordingly. For joint planning method, the EV charging and distribution system are joint planned

simultaneously. In [43], the feasibility of optimally utilizing the potential of the Ontario's grid for charging PHEVs is analysed for off-peak load periods by employing a simplified zonal model of the Ontario's electric transmission network and a zonal pattern of base-load generation capacities for the years from 2009 to 2025. In [44], an environmentally and economically sustainable integration of PHEVs into a power system is addressed under a robust optimization-based planning methodological framework taking the constraints of both power systems and transport sectors into account.

2.1.3 The planning framework in coupled transportation and distribution system

Over the past few years, a significant amount of literatures has proposed methodologies to plan the charging facilities of EVs. However, only a few published papers regarding EV charging station planning consider both transportation and electrical constraints. In [45], the allocation of public charging station is optimized to maximize the social welfare and an equilibrium modelling framework was proposed in a coupled transportation and power network. It is assumed that the electricity prices on transmission nodal will influence the charging behaviours of drivers and therefore influence the traffic flow. However, the nodal electricity prices may hardly influence traffic flow since there is usually a long geographical distance between two transmission nodes and the costs for a PEV to travel from one node to another is high. In [46], a multi-objective PEV charging station planning method was proposed to ensure charging service while reducing power losses and voltage deviations in distribution networks. The FCLM was used and a heuristic simulation procedure was adopted to consider driving range constraints. In [47], the authors studied coordinated planning for integrated power distribution networks and PEV charging systems based on a multi-objective evolutionary algorithm. The authors used the FCLM to consider transportation constraints, while the driving range constraint was ignored. Additionally, [46], [47] consider low voltage distribution networks with service radiuses much smaller than a typical PEVs' driving range, so that the optimality of the planning results was not guaranteed. Reference [48] proposed a mixed-integer non-linear programming model for optimal siting and sizing of PEV charging stations solved by a genetic algorithm. The PEV charging demands were simply assumed to be uniformly distributed across the target area. In [49], the authors studied charging station siting which balances the benefits of PEV owner, charging station owner, and power grid operator. The effect of PEV charging on the power grid was simply assumed to be proportional to the charging power. This research work studies optimal planning of highway PEV fast charging stations and a capacitated flow-refuelling location model (CFRLM) is proposed, in which the PEVs' driving range constraint is explicitly incorporated.

2.1.4 BSS Planning

BSS is regarded as an alternative of FCS, especially in high-density population areas. especially in highdensity population areas. Compared with FCS, charging battery could be completed in minutes and the batteries could be charged during off-peak hours.

BSS receives increasing concerns in the past few years. And the planning and operation issues of BSS has been discussed by many research works [50-63]. [62] presents a framework for optimal design of battery charging/swapping stations in distribution networks based on life cycle cost analysis. [63] can guide planning and construction of battery changing stations in the target city transportation system with construction and transportation cost minimized.

2.2 Joint Planning of EV Charging System, DG and Electricity Network

The renewable resources in DS can be regarded as DG generally and the optimal planning of DG can be regarded as the optimal allocation of renewable resources. The renewable generation is an important alternative of traditional centralized generation. As specified in section 1.1, the increasing load and charging demand from EV require the expansion and reinforcement of substation and electricity network. In this case, DG can be a feasible option to defer the system upgrade investment and become an alternative of the traditional centralized generation. Properly installed DGs can bring benefits, such as system loss reduction, peak load shaving, voltage deviation control and investment deferral. Some significant benefits of DGs are investigated in [64].

However, integrating the DG into EV charging system and distribution network planning means bring new challenges to the system planning methodology. The widespread adoption of intermittent solar PV sources can increase the pressure on the distribution system, especially power fluctuations, reverse power flows, voltage rises and high-power losses. Additionally, the cost of renewable generation and other subsequence investment is another issue to be considered.

2.2.1 DG Planning in Electricity Network

The methodology of DG planning has been discussed in many literatures for a long time and become more complicated and comprehensive in recent years. For DG planning objective, different research works focus on different area to achieve optimization. Some research [65-67] focus on minimization of the network energy losses and [68] determine the optimal placement of DGs for loss reduction and voltage improvement in distribution systems. Some research papers consider the power quality and reliability [69-70] in their objective function. Some literatures build optimization models to minimize the cost and further consider the investment deferral [71-72]. Furthermore, some literatures [73] considered thesis objectives comprehensively and multi-objective function is formed in DG allocation problem.

Additional important factor to be considered is the uncertainty in DG planning. The probabilistic nature of solar irradiance is described using the probability density function PDF in [74] and this model has been used in PV studies [75-78]. Some research papers are based on deterministic methods [66, 68, 70]. [65,79] use analytical methods to determine the optimal location of DG in radial and networked systems.

2.2.2 Distribution system planning with DG Integration

Considering the benefits of DG integration, some researchers have investigated the distribution system expansion planning considering the integration of DGs. [80] proposed a single-stage DS planning model considering DGs for peak load shaving to improve the investment and utilization efficiency. [81] implement DG as a possible alternative for DS construction and reinforcement in a deregulated electricity market environment. Multi-stage dynamic planning models are developed in [82-85] with the integration of DGs.

2.2.3 EV Charging System Planning with DG Integration

Integrating renewable power with EV charging stations has been a research hotspot over recent years. Most of the published papers focus on economic benefit evaluation or coordinated control strategies: [86] adopts EV BSS to accommodate PV generation. [87] studies the economic benefit of integrating PV generation with FCS. [88-89] demonstrates that coordinated PEV charging could significantly promote distributed PV power integration. [90] confirms that coordinated PEV charging could alleviate voltage rise problems caused by PV penetration.

Recently, some research works tried to explore the joint planning of EV charging stations and renewable power generations: [91] studies design of on-site PV panels and BSS. The capacities of PV panels, PEV batteries, and number of PEV chargers are optimized at the same time. [92] proposes a multi-stage, multi-objective planning algorithm for uncoordinated PEV charging posts and renewable generation. [93] develops a multi-objective model to optimize the siting and sizing of charging stations and distributed renewable generation in DS. [94] designed a PEV charging station for work place powered by PV generation with vehicle-to-grid (V2G) technology. [95] studies the reactive power support in optimization of a PEV charging station with grid-integrated PV system. [96] proposes a two-stage optimization method to simultaneously allocate EV charging stations with DG in DS.

2.3 V2G Function and Coordinated Charging Control Strategy

Recently, a lot of interests have been directed towards V2G and coordinate charging strategies to mitigate the negative influences of the large-scale penetration of EVs and fully explore the potential benefits from EV integration. [97-99] investigate the impacts of EV charging on distribution systems. Coordinated charging and discharging strategies are proposed in [100-103] to optimally charge the EVs. EV charging control methods for V2G functionality were developed in [104-105] and the concept of EV aggregator which act as a virtual agent between grid and EVs is investigated in [106-108] to provide ancillary services. EV charging is jointly dispatch with renewable energy generation in [109]. PHEV control strategies were analysed in [110-112]. These studies provide a market mechanism for EV owners to participate in grid-support services.

The planning issue of EV charging system considering the charging control strategies has also been investigated in several literatures. In [113], the optimal sizing and siting of a PEV charging station with vehicle-to-grid capabilities in distribution networks was studied. The distribution planning considering the coordinated charging strategy of EVs is explored in [43].

However, challenges exist in terms of achieving V2G and coordinated charging strategy. Generally, drivers expect to refuel their EVs as soon as possible, uncontrollable driving behaviours and the stochastic nature of charging profile make the implementation of centralized charging or discharging control a hard work. In this case, some incentive strategies are required to promote the EV drivers' acceptance.

2.4 Uncertainty Analysis in System Planning

Uncertainty is an important problem to be solved in the planning issue. The uncertainties of power system planning may include deviations caused by market, price, demand, policy and new technology integration. And the uptake rate of EVs in the markets can be determined by different factors, to namely purchase price, driving range, battery capacity, maximum speed, charging infrastructure, government decisions, etc. Some uncertainties, such as the stochastic power demand of a PEV due to its random charging and discharging schedule, generation from wind power unit due to the frequently variable wind speed, and solar generating source due to the stochastic illumination intensity, volatile fuel prices, and future uncertain load growth could lead to some risk in determining the optimal system planning. Many

research works have made efforts to uncertainty analysis and corresponding risks in power system planning.

The most commonly used methods to deal with uncertainties are mathematical-statistical models and Monte Carlo simulations with probabilistic/stochastic models. Probabilistic/stochastic models are widely proposed to deal with uncertainties, such as [114-119]. Probabilities density functions (PDFs) are derived based on the empirical data. The target of stochastic programming is to maximize the expectation of the decisions (possible plans) and the random variables (market uncertainties). These approaches are reasonable when the uncertainties of estimates, weights and probabilities are low. However, computation burdens are heavy for reaching the convergence of result. This is more serious when a system is complex. Besides, when historic data is insufficient, it is difficult to draw accurate PDFs to simulate those uncertainties.

Decision analysis [120] is another approach to deal with random uncertainties. The first step is to identify several future scenarios, based on market forecasts, or expert knowledge. Then an optimal plan is searched under each scenario. The objective difference between a possible plan and the optimal plan is called regret, which measures the risks of a possible plan under other scenarios. If the regret for a plan is zero, then the plan is robust. If there is no robust plan, a choice should be made among those possible plans, such as minimize the maximum regret, maximize the benefit, or minimize the average regret. These ideas are also extended for the multi-objective problems.

Fuzzy decision method can be employed to obtain the optimization result when the weighting of different stakeholders and planning objective are hard to be evaluated [121-123]. Fuzzy decision method is based on a rule-based decision-making mechanism that incorporates different judgments involving experience and opinions. Those judgments are described in qualitative terms and a variety of conflicting requirements are needed to be balanced. Planning decision making procedure needs to be supplemented by fuzzy set theory [124].

Additionally, adaption cost is proposed to quantify future uncertainties [125]. Adaption cost is defined as the additional capital investments required for a proposed plan when changes happen in proposed scenario. This uncertainty compensation method has been employed in electric generation portfolios [126] and flexible transmission expansion planning [127-130]. The flexibility criterion reflects the adaption capability of a plan to adapt into any potential scenarios at minimum costs. [43] extend this method into DS planning considering the integration of PEV.

The content of this thesis is summarized as below:

Chapter 1 introduces the background of EV and EV charging system. The challenges existing in the EV charging system planning are also discussed. Chapter 2 lists and compares the existing research works related to the EV charging facilities planning. Chapter 3 discussed the existing and proposed methodologies to be used in the EV charging system planning optimization model and analysis process. Chapter 4 propose a joint planning framework for Electric-Vehicle charging system and power system network. In this model, the uncertainties of Electrical-Vehicle charging load profile is analysed. Based on the model in Chapter 5, Chapter 6 consider the renewable generation planning in power system. An Energy Management System of Smart Building with Electric Vehicle, Photovoltaic and Battery Energy Storage is proposed in Chapter 7 to discuss the charging behaviour of parking Electric-Vehicle.

Chapter 3 Methodology in EV Charging System Planning

3.1 Queuing Theory in FCS

The queuing modelling can be used to evaluate the waiting time for charging service, determine the optimal capacity of the charging facilities and further calculate the charging demand of FCS during a time interval. The following introduce different queuing theories can be used to model the charging behaviour of EVs in FCS.

3.1.1 M/M/C Queuing Theory

The charging facilities are assumed to be identical and the EVs are served based on the first-come firstserved rule. M/M/C represent a queuing model [131] in FCS where C represents the capacity. In this model, the arrival sequence is determined by the Poisson Process and the service time follows a negative exponential distribution:

The waiting time of EVs for charging service can be calculated based on the Little's Law:

$$AW_{n,t} = \frac{1}{z_n!} \left(\frac{\lambda_{n,t}}{\mu}\right)^{z_n} \frac{z_n \mu}{\left(z_n \mu - \lambda_{n,t}\right)^2} P_{n,t}^0 \quad \forall n \in \phi^{FCS}, \forall t \in T$$
(3.1)

The steady state probability of the FCS which means that no EVs is under charging service in FCS is described by:

$$P_{n,t}^{0} = \left[\sum_{i=0}^{z_{n}-1} \frac{1}{i!} \left(\frac{\lambda_{n,t}}{\mu}\right)^{n} + \frac{1}{z_{n}!} \left(\frac{\lambda_{n,t}}{\mu}\right)^{z_{n}} \left(\frac{z_{n}\mu}{z_{n}\mu - \lambda_{n,t}}\right)\right]^{-1}$$
(3.2)

The limiting-state probability that there are i numbers discharged EVs in FCS:

$$P_{n,t}^{i} = \begin{cases} \frac{1}{i!} \left(\frac{\lambda_{n,t}}{\mu}\right)^{i} P_{n,t}^{0} & \text{if } 0 \le i < z_{n} \\ \frac{1}{z_{n}! z_{n}^{i-z_{n}}} \left(\frac{\lambda_{n,t}}{\mu}\right)^{i} P_{n,t}^{0} & \text{if } 0 \le i < z_{n} \end{cases}$$
(3.3)

The occupation rate of charging facilities in FCS denotes the probability that a charging facility is under charging service and can be obtained by:

$$\rho_{n,t} = \frac{\lambda_{n,t}}{z_n \mu} \quad \forall n \in \phi^{FCS}, \forall t \in T$$
(3.4)

The number of charging facility under charging service is given by $\min(i, z_n)$ and the expected number of charging facilities under charging service in time step t is defended by:

$$B_{n,t} = \frac{\lambda_{n,t}}{\mu} \quad \forall n \in \phi^{FCS}, \forall t \in T$$
(3.5)

3.1.2 $M/G/C/\infty$ Queuing Theory

The charging facilities are assumed to be identical and the EVs are served based on the first-come firstserved rule. And $M/G/C/\infty$ [132-133] represent a queuing model in FCS where c indicates the capacity and ∞ indicates infinite waiting space. We assume the waiting space is infinity in the planning stage as discussed in [134] to simplify the problem. In this model, the arrival sequence is determined by the Poisson Process and the service time follows PDF:

The waiting time of EVs for charging service can be calculated based on the Little's Law:

$$AW_{n,t}^{M/G/s} = \frac{R_D(1+c_{\mu}^2)}{(2R_D-1)c_{\mu}^2+1}AW_{n,t}^{M/M/s}$$
(3.6)

$$AW_{n,t}^{M/M/s} = \frac{1}{z_n!} \left(\frac{\lambda_{n,t}}{\mu}\right)^{z_n} \frac{z_n \mu}{\left(z_n \mu - \lambda_{n,t}\right)^2} \left[\sum_{i=0}^{z_n-1} \frac{1}{i!} \left(\frac{\lambda_{n,t}}{\mu}\right)^n + \frac{1}{z_n!} \left(\frac{\lambda_{n,t}}{\mu}\right)^{z_n} \left(\frac{z_n \mu}{z_n \mu - \lambda_{n,t}}\right)\right]^{-1} \quad \forall n \in \phi^{FCS}, \forall t \in T$$

$$(3.7)$$

where R_D can be calculated by:

$$R_{D} = \frac{1}{2} \left[1 + F\left(\theta\right) (\mu - 1) \left(1 - e^{-\frac{\theta}{F(\theta)(\mu - 1)}} \right) \right]$$
(3.8)

$$F(\theta) = \frac{\theta}{8(1+\theta)} \left(\sqrt{\frac{9+\theta}{1-\theta}} - 2 \right)$$
(3.9)

$$\theta = \frac{z_n - 1}{z_n + 1} \tag{3.10}$$

The occupation rate of charging facilities in FCS denotes the probability that a charging facility is under charging service and can be obtained by:

$$\rho_{n,t} = \frac{\lambda_{n,t}}{z_n \mu} \quad \forall n \in \phi^{FCS}, \forall t \in T$$
(3.11)

3.2 Traffic Flow Modelling

For practical transportation system, the traffic flow of traditional vehicles can be obtained from realtime data [135-136]. However, it is necessary to build the traffic flow assignment model in given transportation system for the EV FCS location problem. Generally, EV drivers usually prefer to travel on the route with the shortest distance between the origin and the destination, and this route can be identified by well-developed Dijkstra or Floyd algorithms [137]. Accordingly, we review and propose different traffic flow assignment model in this part.

3.2.1 Gravity Spatial Interaction Model (GSI)

The GSI model can be used to generate the origin-destination (OD) flow artificially to reflect the flow infrastructure of the transportation system based on the node weights and link length [138-140]. The weight of the node in transportation system is physically represent the ability of the node to attract the traffic flow.

The mathematical formulation can be described by:

$$A_{rs} = 1.5 \times \frac{W_r^T W_s^T}{d_{rs}^T}, \quad \forall r \in N^T, s \in N^T, r \neq s$$
(3.12)

$$f_{t}^{rs} = EV_{t}^{Total} \frac{A_{rs}}{\sum_{rs \in Q} A_{rs}} \quad \forall r \in N^{T}, s \in N^{T}, r \neq s$$
(3.13)

3.2.2 User Equilibrium based Traffic Assignment Model (UETAM)

The UETAM was introduced in [141]. The traffic on a path in transportation network can be obtained based on the UETAM at each time interval. The formulation of the mathematical model is presented as the following:

The objective function is to solve the equilibrium problem by minimizing the sum of integrals of the link performance function.

Objective Function:

$$Minimization: f(x) = \sum_{m \in A^{T}} \int_{0}^{f_{m,t}^{T}} PF(f) df = \sum_{m \in A^{T}} t_{m}^{0} \left[f_{m,t}^{T} + 0.03 \left(\frac{\left(f_{m,t}^{T} \right)^{5}}{\left(c_{m}^{T} \right)^{4}} \right) \right]$$
(3.14)

The link performance function in this case is defined as the flow-dependent travel time and can be solved based on the formula proposed by Bureau Public Roads (BPR). This link performance evaluation method considers both the length of the link and the traffic congestion effects:

$$t_{m,t}^{T} = t_{m}^{0} \left[1 + 0.15 \left(\frac{\left(f_{m,t}^{T} \right)^{4}}{\left(c_{m}^{T} \right)^{4}} \right) \right], \quad \forall m \in A^{T}$$
(3.15)

The flow-based travel time of the associated path can be calculated by:

$$t_{q,t}^{rs} = \sum_{m \in A^T} \left(\delta_{m,q}^{rs} \times t_{m,t}^T \right), \quad \forall q \in Q_{rs}, r \in N^T, s \in N^T$$
(3.16)

Subject to:

The flow conservation constraints which denotes the sum of the flows on all the possible paths connecting rs should equal to the trip rate of the OD pair rs:

$$\sum_{q\in\mathcal{Q}_{rs}}f_{q,t}^{rs}=f_t^{rs},\quad\forall r\in N^T,s\in N^T$$
(3.17)

The flow on each link:

$$f_{m,t}^{T} = \sum_{r \in N^{T}} \sum_{s \in N^{T}} \sum_{q \in \mathcal{Q}_{rs}} \left(\delta_{m,q}^{rs} \times f_{q,t}^{rs} \right), \quad \forall m \in A^{T}$$
(3.18)

The UETAM is a nonlinear programming problem which could be solved in advance by primal-dual interior point method.

3.2.3 Probabilistic Based UETAM

Previous research generally uses the traffic flow of traditional vehicles for simulation. However, it could not fully describe the driving behaviour of EV in the future transportation network. Therefore, in this part, we develop a Probability based UETAM to model the traffic flow of EVs in transportation system with the mutual interaction between traffic flow patterns, traffic congestion and the location of the fast charging facilities incorporated. In determining the network traffic flow pattern, a stochastic user equilibrium principle is applied to model drivers' routing choice behaviours. The decision variables of the user equilibrium model include the location plan of FCS, as well as the equilibrium flow pattern, both of which are obtained endogenously from the model solution. It is reasonable to make the consumption that drivers could have access to the transportation information and FCS location due to the increasing use of on-board vehicle navigation system.

The mathematical formulation of Probability based UETAM is:

The flow on each link:

$$f_{m,t}^{T} = \sum_{r \in N^{T}} \sum_{s \in N^{T}} \sum_{q \in \mathcal{Q}_{rs}} \left(\delta_{m,q}^{rs} \times f_{q,t}^{rs} \right), \quad \forall m \in A^{T}$$
(3.19)

The flow-dependent travel time considering the length of route and the traffic congestion effects.
$$t_{m,t}^{T} = t_{m}^{0} \left[1 + 0.15 \left(\frac{\left(f_{m,t}^{T} \right)^{4}}{\left(c_{m}^{T} \right)^{4}} \right) \right], \quad \forall m \in A^{T}$$
(3.20)

$$t_{q,t}^{rs} = \sum_{m \in A^T} \left(\delta_{m,q}^{rs} \times t_{m,t}^T \right), \quad \forall q \in Q_{rs}, r \in N^T, s \in N^T$$
(3.21)

The probability of travellers' routing choice considering the availability of FCS and the flow-dependent travel time.

$$g_{q,t}^{rs} = \frac{\exp\left(\alpha^{time}t_{q,t}^{rs} + \beta^{FCS}\tau_{q}^{rs}\right)}{\sum_{rs\in\mathcal{Q}_{rs}}\exp\left(\alpha^{time}t_{rs,t}^{rs} + \beta^{FCS}\tau_{rs}^{rs}\right)}, \quad \forall q \in \mathcal{Q}_{rs}, r \in N^{T}, s \in N^{T}$$
(3.22)

The probabilistic assignment of traffic flow on each candidate path:

$$f_{q,t}^{rs} = f_t^{rs} g_{q,t}^{rs}, \quad \forall q \in Q_{rs}, r \in N^T, s \in N^T$$
(3.23)

3.3 EV Charging System Location Optimization Methods

In traffic and logistic research, well-established methods such as the location theory have been developed that allow analysts and decision-makers to explore trade-offs among different objectives and to analyse the impacts of constraints on the decision-making of facility locations and capacities [142]. And in charging system planning, the site and size of charging facility could influence the convenience of charging service and further impact on the economic benefit of the operator. Therefore, we expect to maximize the captured charging demand in planning framework of EV charging station.

3.3.1 Maximal Covering Location Model (MCLM)

A portion of the research [143-146] can be classified as the maximal covering location problem, which seeks to maximize demand coverage by locating a certain number of facilities. However, the MCLM deals with static demands at nodes and does not include the mobility nature of vehicles. This method is more suitable for the location problem of low or medium voltage charging post.

In this model, the charging demand in a certain area is estimated and assigned to the associated node. Given this assumption, the objective of charging facility location planning in the network is to maximally serve the demand at these nodes. This planning model can be mathematically formulated as follow:

Objective Function:

The objective function is to be maximized for the number of covered demands.

$$Maximization: F = \sum_{t \in T} \sum_{n \in N^T} D_{n,t}^{CP} \tau_n$$
(3.24)

Subject to:

The charging demand at node n cannot be covered unless at least one of the selected facility sites that could cover the demand at node n. This is generally determined by the service radius and the selection of candidate facilities.

$$\sum_{n \in N^{T}} c_{nn} \alpha_{m}^{CP} \ge \tau_{n}, \forall n \in N^{T}$$
(3.25)

The covered demand at node n during time step t is determined by the total demand for charging post service and constrained by the size of charging post located at node n.

$$D_{n,t}^{CP} = \begin{cases} D_{n,t}^{Total} & \text{if } D_{n,t}^{Total} \le \mathbf{S}_n^{CP} P^{CP} \\ \mathbf{S}_n^{CP} P^{CP} & \text{if } D_{n,t}^{Total} > \mathbf{S}_n^{CP} P^{CP} \end{cases}$$
(3.26)

The limitation for the total number of charging post facilities:

$$\sum_{n \in N^T} \alpha_n^{CP} \mathbf{S}_n^{CP} = N_{Total}^{CP}$$
(3.27)

This model considers the network geographical information as well as the nodal demand differences and can be used to in the allocation of charging post which generally serve the demand at fixed location. However, the charging demand is simulated as static and fixed at each node, which could not fully describe the dynamic and mobile nature of EVs' on-route charging. And therefore, the static node demand oriented modelling in maximal covering location model cannot reflect the complexities of EV fast charging demand and is inappropriate in fast charging station planning.

3.3.2 Flow Capturing Location Model (FCLM) – For Small-Scale Transportation System

Small scale transportation system is located at small or medium area where the daily driving distance is comparably small. For Fast Charging Station Planning in small scale transportation system, the consumption of battery storage on a route is not evident and therefor it is not necessary to consider the change of SOC along the route. The flow capturing location models described in this part is to select site and size of charging facilities to fulfil the flow-based charging demand.

Because of the nature of EVs' mobility, the number of EVs for charging service in transportation system is time-varying and this depends on a variety of factors, such as the driving behaviours of individual EVs, local traffic conditions, as well as the SoC of EV battery. This on-route charging demand is hard to estimate because of the diversified travelling patterns and the lack of relevant EV driving statistical numbers. In this case, the captured traffic flow inside the traffic network can be an indicator of the convenience of charging service, the market potential of entity and the charging demand of FCS.

3.3.2.1 FCLM

The traffic flow of EV is defined by the number of EVs travelling along the lines or edges connecting the different nodes along the pre-determined travel route. If a charging station is located on the travel route of a certain EV, then the EV may choose to obtain charging service there. In this case, it is expected that fast charging station can serve as many EVs as possible. The traffic network topology, traffic system condition and driving patterns can be well addressed in FCLM for the travelling and charging

convenience. This model is based on the flow-capturing location model [147-148]. And the mathematical framework is:

The objective function is to maximize the total captured traffic flow that could be charged by the candidate stations:

$$Maximization: F = \sum_{r \in N^T} \sum_{g \in Q_{rs}} \tau_q^{rs} \times 365 \times \sum_{t \in T} f_{q,t}^{rs}$$
(3.28)

Accordingly, the traffic flow captured by candidate fast charging station in time t can be calculated by:

$$f_{n,t}^{FCS} = \sum_{r \in N^T} \sum_{g \in Q_n} \sum_{q \in Q_n} f_{q,t}^{rs} \delta_{n,q}^{FCS} \alpha_n^{FCS}$$
(3.29)

$$\delta_{n,q}^{FCS} = \begin{cases} 1 & \text{if } n \in Q_{rs} \\ 0 & Otherwise \end{cases}$$
(3.30)

Subject to:

The traffic flow on path q connecting the OD pair rs can be captured only if at least one FCS exists on path q.

$$\tau_q^{rs} = \begin{cases} 1 & \text{if Fast Charging Station exists on path q} \\ 0 & \text{if no Fast Charging Station exists on path q} \end{cases}$$
(3.31)

$$\sum_{n \in \phi_q^{FCS}} \alpha_n^{FCS} \ge \tau_q^{rs}$$
(3.32)

3.3.2.2 Location Constrained FCLM

The FCLMs proposed in the previous literature determine traffic flow assignment on the network by assigning the OD demand to the shortest path or least-cost path. This based on the assumption that travellers' routing choice behaviour is governed only by the travel distance or the time cost. However, the construction of FCS may influence the route selection of drivers and further influence the traffic flow. It is important for the location model to capture the EV drivers' routing choice behaviour which effect the optimal location of charging facilities and further determine the charging demand from FCS. In this case, we propose two models: deviation-flow capturing recharging location model and stochastic use equilibrium based flow capturing location model.

1) Deviation based FCLM

The key aspect of this model is that the driver will deviate from the pre-determined path to recharge their vehicles at the nearest FCS if the SoC of EV battery lower than the threshold. With the increasing use of on-board vehicle navigation systems, it is reasonable to assume that drivers could take the shortest or least cost path to their target recharging stations and then to their destination. This model could better reflect the driving behaviour of EVs when the FCS network is sparse and can better evaluate the effects on distribution network from the charging load of FCS.

The objective function is to maximize the total captured traffic flow that could be charged by the candidate recharging stations. The first part evaluates the number of EVs that receive charging service on predetermined route and the second part calculate the total number of EVs that will reselect the route for charging service.

Objective Function:

$$Maximization: F = 365 \times \left[\sum_{r \in N^T} \sum_{s \in N^T} \sum_{q \in Q_{rs}} \left(\tau_q^{rs} \times g_q^{char} \times \sum_{t \in T} f_{q,t}^{rs} \right) + \sum_{r \in N^T} \sum_{s \in N^T} \sum_{q \in Q_{rs}} \left((1 - \tau_q^{rs}) \times g_q^{dev} \times \sum_{t \in T} f_{q,t}^{rs} \right) \right]$$
(3.33)

Accordingly, the traffic flow captured by candidate fast charging station in time t can be calculated by:

$$f_{n,t}^{FCS} = \sum_{r \in N^T} \sum_{s \in N^T} \sum_{q \in Q_{rs}} f_{q,t}^{rs} g_q^{char} \delta_{n,q}^{FCS} \alpha_n^{FCS} + \sum_{r \in N^T} \sum_{s \in N^T} \sum_{q \in Q_{rs}} f_{q,t}^{rs} g_{qd}^{dev} \delta_{n,qd}^{FCS} \alpha_n^{FCS}$$
(3.34)

Subject to:

the traffic flow on path q connecting the OD pair rs can be captured only if at least one Fast Charging Station exists on path q.

$$\tau_q^{rs} = \begin{cases} 1 & \text{if FCS exists on path } q \\ 0 & \text{if no FCS exists on path } q \end{cases}$$
(3.35)

$$\delta_{n,q}^{FCS} = \begin{cases} 1 & if \text{ the node n FCS exists on path } q \ (n \in \phi_q^{Node}) \\ 0 & Otherwise \end{cases}$$
(3.36)

$$\delta_{n,qd}^{FCS} = \begin{cases} 1 & \text{if the node n FCS exists on the deviation path qd} (n \in \phi_{qd}^{Node}) \\ 0 & Otherwise \end{cases}$$
(3.37)

$$\sum_{n \in \phi_q^{FCS}} \alpha_n^{FCS} \ge \tau_q^{rs}$$
(3.38)

The fraction of EV flow that will transfer to the deviation path is determined by the extra distance for charging service and the existing SoC of EVs. And we use sigmoid fitting curve is used to compute the fraction. And the parameters can be specified based on the survey.

$$g_q^{char}(SoC_q^{EV}) = \frac{1}{1 + \exp\left(\beta SoC_q^{EV}\right)}$$
(3.39)

$$g_{qd}^{dev}(SoC_q^{EV}, d_{qd}^{extra}) = \frac{1}{1 + \exp\left(\alpha d_{qd}^{extra} + \beta SoC_q^{EV}\right)}$$
(3.40)

The distribution of EVs' SoC is determined by normal fitting method based on the central limit theorem in probability theory [8]. And we use the MC simulation to generate the random SoC of EVs driving on the routes.

$$p(SoC^{EV}, \mu^{SoC}, \sigma^{SoC}) = \frac{1}{\sigma^{SoC}\sqrt{2\pi}} \exp\left(-\frac{(\mu^{SoC} - SoC^{EV})^2}{2(\sigma^{SoC})^2}\right)$$
(3.41)

2) Probabilistic FCLM

The mutual interaction between traffic flow patterns, traffic congestion and the location of the fast charging facilities is incorporated in this model. In determining the network traffic flow pattern, a stochastic user equilibrium principle is applied to model drivers' routing choice behaviours. The decision variables of the user equilibrium model include the location plan of FCS, as well as the equilibrium flow pattern, both of which are obtained endogenously from the model solution. Accordingly, we could assign the traffic flow in the network considering both travel time and availability of charging facilities.

In this model, the following assumptions are made:

- To reduce the complexity of the model, we only consider the EVs in the network.
- A route flow is captured if the vehicles on that route can receive the charging service during the trip.

The formulation of the mathematical model is presented as the follows:

The objective function is to maximize the total captured traffic flow that could be charged by the candidate recharging stations:

$$Maximization: F = 365 \times \left[\sum_{r \in N^T} \sum_{s \in N^T} \sum_{q \in Q_{rs}} \left(\tau_q^{rs} \times \sum_{t \in T} f_{q,t}^{rs} \right) \right]$$
(3.42)

Accordingly, the traffic flow captured by candidate fast charging station in time step t can be calculated by:

$$f_{n,t}^{FCS} = \sum_{r \in N^T} \sum_{s \in N^T} \sum_{q \in \mathcal{Q}_{rs}} f_{q,t}^{rs} \delta_{n,q}^{rs} \alpha_n^{FCS}$$
(3.43)

Subject to:

the traffic flow on path q connecting the OD pair rs can be captured only if at least one FCS exists on path q.

$$\tau_q^{rs} = \begin{cases} 1 & \text{if FCS exists on path } q \\ 0 & \text{if no FCS exists on path } q \end{cases}$$
(3.44)

$$\sum_{\substack{n \in \phi_q^{FCS}}} \alpha_n^{FCS} \ge \tau_q^{rs}, \quad \forall q \in Q_{rs}, r \in N^T, s \in N^T$$
(3.45)

The traffic flow $f_{q,t}^{rs}$ in objective function is given exogenously based on the following user equilibrium principal. The flow on each can be described as follow:

$$f_{m,t}^{T} = \sum_{r \in N^{T}} \sum_{s \in N^{T}} \sum_{q \in \mathcal{Q}_{rs}} \left(\delta_{m,q}^{rs} \times f_{q,t}^{rs} \right), \quad \forall m \in A^{T}$$
(3.46)

The flow-dependent travel time considering the length of route and the traffic congestion effects.

$$t_{m,t}^{T} = t_{m}^{0} \left[1 + 0.15 \left(\frac{\left(f_{m,t}^{T} \right)^{4}}{\left(c_{m}^{T} \right)^{4}} \right) \right], \quad \forall m \in A^{T}$$
(3.47)

$$t_{q,t}^{rs} = \sum_{m \in A^T} \left(\delta_{m,q}^{rs} \times t_{m,t}^T \right), \quad \forall q \in Q_{rs}, r \in N^T, s \in N^T$$
(3.48)

The probability of travellers' routing choice considering the availability of FCS and the flow-dependent travel time.

$$g_{q,t}^{rs} = \frac{\exp\left(\alpha^{time}t_{q,t}^{rs} + \beta^{FCS}\tau_{q}^{rs}\right)}{\sum_{rs\in Q_{rs}}\exp\left(\alpha^{time}t_{rs,t}^{rs} + \beta^{FCS}\tau_{rs}^{rs}\right)}, \quad \forall q \in Q_{rs}, r \in N^{T}, s \in N^{T}$$
(3.49)

The probabilistic assignment of traffic flow on each candidate path:

$$f_{q,t}^{rs} = f_t^{rs} g_{q,t}^{rs}, \quad \forall q \in Q_{rs}, r \in N^T, s \in N^T$$
(3.50)

3.3.2.3 Battery Capacity Constrained FCLM

In this model, we use the captured EVs for charging service on different travelling route to model the charging demand and power consumption of FCS, rather than simply calculate the captured traffic flow. The number of EVs with charging demand is estimated based on the stochastic modelling of SoC of EV flow and the service capability of Fast Charging Station is incorporated with queuing theory.

The objective function is to maximize the total captured traffic flow that could be charged by the candidate stations:

$$Maximization: F = 365 \times \sum_{t \in T} \lambda_{n,t}$$
(3.51)

$$\lambda_{n,t} = \sum_{r \in N^T} \sum_{s \in N^T} \sum_{q \in \mathcal{Q}_{rs}} g_q^{char} f_{q,t}^{rs} \delta_{n,q}^{FCS} \alpha_n^{FCS}$$
(3.52)

In this objective function, $\lambda_{n,t}$ denotes the traffic flow captured by candidate FCS located at node n in time t. This variable is dependent on the number of EVs traffic flow with charging intention and constrained by the capacity of FCS.

The FCS capacity dependent average waiting time of EVs at node n in time t is constrained by the maximum waiting time:

$$AW_{n,t}(z_n) \le \overline{AW} \tag{3.53}$$

The waiting time of EVs for charging service can be calculated based on the Little's Law:

$$AW_{n,t} = \frac{1}{z_n!} \left(\frac{\lambda_{n,t}}{\mu}\right)^{z_n} \frac{z_n \mu}{\left(z_n \mu - \lambda_{n,t}\right)^2} \left[\sum_{i=0}^{z_n-1} \frac{1}{i!} \left(\frac{\lambda_{n,t}}{\mu}\right)^n + \frac{1}{z_n!} \left(\frac{\lambda_{n,t}}{\mu}\right)^{z_n} \left(\frac{z_n \mu}{z_n \mu - \lambda_{n,t}}\right)\right]^{-1} \quad \forall n \in \phi^{FCS}, \forall t \in T$$

$$(3.54)$$

Based on the survey from [149], the probability of users for charging service follows negative exponential distribution as shown in figure 3.1 and we use sigmoid fitting curve to simulate it with the parameters specified based on the survey.

$$g_q^{char}(SoC_q^{EV}) = \frac{1}{1 + \exp\left(\beta SoC_q^{EV}\right)}$$
(3.55)

The distribution of EVs' SoC is determined by normal fitting method based on the central limit theorem in probability theory [150]. And we use the MC simulation to generate the random SoC of EVs driving on the routes.



$$p(SoC^{EV}, \mu^{SoC}, \sigma^{SoC}) = \frac{1}{\sigma^{SoC} \sqrt{2\pi}} \exp\left(-\frac{(\mu^{SoC} - SoC^{EV})^2}{2(\sigma^{SoC})^2}\right)$$
(3.56)



3.3.3 Flow Recharging Location Model (FRLM) – For Large-Scale Transportation System

The FRLM extends the FCLM and incorporates the battery capacity and driving range constraints of EVs. The planning target of FRLM is generally long-distance driving in transportation network with large service radius, like highway, motorway and freeway. Additionally, the EV drivers in long-distance transportation network prefer to charge their vehicles on the way during a trip as it is not efficient to perform a dedicated travel to procure charging service alone. However, the irrational placement of EV FCS with respect to the traffic network will lead to extra driving distance potential exceeding EV's driving capability. In this case, the battery capacity, traffic network and the driving pattern are included in the FRLM for the proper allocation of EV charging station.

The Flow Refuelling Location Model is proposed in [151] and this model is further used in [152-153] to solve the refuel station location problem. [154-155] suggest a heuristically algorithm to solve the Flow Refuelling Location Model and [156-159] propose alternative formulations to allow the model can be mathematically formulated efficiently. A network expansion method is incorporated in the Flow Refuelling Location Model in [160] to improve the computability of the model and this method is the basis of The FRLM proposed and refined in the following research.

3.3.3.1 FRLM

In this section, we review the driving range logic and the corresponding flow refuelling location model proposed in [159] which are the base for the FRLM in the following research.

A. SoC Check Logic of EV Traffic Flow

If EV reach a node with a charging station along the route, EV can then be fully charged and continually driving towards the destination. If there is not enough energy for EV to finish the pre-determined route, the allocation framework cannot charge EVs along this route. If EVs can move from the origin to the destination without running out of energy along the route, the route is considered chargeable by the allocated charging stations. The EV SoC check logic for the traffic flow is described in this section and whether the traffic flow on a specific route could be sufficiently charged or not could be determined with this procedure repeated for every possible travel routes of EVs.

We first consider a transportation network as shown in figure 3.2 that consists of a single path q. The EV enter the transportation network with SoC_{o} and leave the network with SoC_{o} . The SoC_{o} should be

higher than SoC_D because the distance between the destination and the exit of the transportation network. In this case, we add a source node r and sink node s to build an expanded transportation network $\phi(N^q, A^q)$. The distance related to the source node and sink node is determined by the corresponding SoC_D and SoC_D .



Fig. 3.2 Network Expanding Theory

Accordingly, we build the set of reachable arcs A^q of path q by connecting any two nodes i, j if the ordering index of node i is less than node j, and node j can be reached from node i after a single charge. Each path in A^q characterizes a feasible solution for FCS location. Additionally, we also add a pseudo arc arc(rs) that directly connect the source node r and sink node s to the set of reachable arcs. This pseudo arc is used to capture the unsatisfied charging demand with no feasible path to travel through the route.

$$arc(ij) \in A^{q} \quad if \begin{cases} d^{q}(i, j) \leq R^{EV} \\ \text{and} & \forall i, j \in N^{q} \\ ord^{q}(i) < ord^{q}(j) \end{cases}$$
(3.57)
$$arc(rs) \in A^{q}$$

Based on the above method, we could construct the $\phi(N, A)$ by repeat the same procedure for all available paths Q in the transportation network.

$$N = \bigcup_{q \in Q} N^{q} \quad and \quad A = \bigcup_{q \in Q} A^{q}$$
(3.58)

B. Flow Refuelling Location Model

Based on the expanded transportation network, the Flow Refuelling Location Model can be formulated in two different types with different objective.

The first objective is to optimally locate FCS to maximize the total flow covered and the corresponding FRLM can be formulated as follow:

$$Maximization: F = 365 \times \sum_{q \in Q} f_q^{rs} (1 - x_{rs}^q)$$
(3.59)

Subject to:

$$\sum_{\{j|(i,j)\in A^{q}\}} x_{ij}^{q} - \sum_{\{j|(j,i)\in A^{q}\}} x_{ji}^{q} = \begin{cases} 1 & \text{if } i = r^{q} \\ -1 & \text{if } i = s^{q} \\ 0 & \text{if } i \neq r^{q} s^{q} \end{cases} \quad \forall i \in N^{q}, q \in Q$$
(3.60)

$$\sum_{\{j|(j,i)\in A^q\}} x_{ji}^q \le \alpha_i^{FCS} \quad \forall i \in N^q, q \in Q$$
(3.61)

$$x_{ii}^q \ge 0 \quad \forall (i,j) \in A^q, q \in Q \tag{3.62}$$

The second objective is to optimally locate FCS to minimize the total cost of FCS construction and the corresponding FRLM can be formulated as follow:

$$Minimization: F = \sum_{q \in Q} \sum_{i \in N^q} C_i^{FCS} \alpha_i^{FCS}$$
(3.63)

Subject to:

$$\sum_{\{j|(i,j)\in A^{q}\}} x_{ij}^{q} - \sum_{\{j|(j,i)\in A^{q}\}} x_{ji}^{q} = \begin{cases} 1 & \text{if } i = r^{q} \\ -1 & \text{if } i = s^{q} \\ 0 & \text{if } i \neq r^{q} s^{q} \end{cases} \quad \forall i \in N^{q}, q \in Q$$
(3.64)

$$\sum_{\{j|(j,i)\in A^q\}} x_{ji}^q \le \alpha_i^{FCS} \quad \forall i \in N^q, q \in Q$$
(3.65)

$$x_{ij}^q \ge 0 \quad \forall (i,j) \in A^q, q \in Q \tag{3.66}$$

3.3.3.2 Stochastic FRLM – For Freeway Network

The enter and exit nodes of route in large scale transport network is most likely different from the driver's departure and destination point. All vehicles are assumed to have same SoC or fully charged when they start their trip in conventional FCLM used in [161-163]. However, the fact is that EVs have different SoC at the start and exit nodes in transportation network. This can affect the optimal location of FCS along the route and should be considered in FRLM. And in this section, we use a stochastic way to simulate the dynamic nature of the SoC of the Traffic Flow and incorporate the stochastic SoC of EV flow into the FCLM.

A. Distribution of EV SoC

In this section, a stochastic approach is deployed to simulate the past travel range and the corresponding SoC of EV. The distribution of past driving range is determined by normal fitting method based on the central limit theorem in probability theory [164]:

$$p(R_{o}^{EV}, \mu_{o}^{R}, \sigma_{o}^{R}) = \frac{1}{\sigma_{o}^{R} \sqrt{2\pi}} \exp\left(-\frac{(R_{o}^{EV} - \mu_{o}^{R})^{2}}{2(\sigma_{o}^{R})^{2}}\right)$$
(3.67)

Accordingly, SoC is assumed linearly proportional to the driving range and the estimation of SoC of the EV at entering point of transportation route can be derived from:

$$SoC_o^{EV} = (1 - \frac{R_o^{EV}}{R^{EV}}) \times 100\%$$
 (3.68)

The distance R_D^{EV} between the exit node of the transportation network and the driver's destination follow the normal distribution as well and therefore the minimum SoC at the exit node SoC_D^{EV} can be determined.

B. EV Flow SoC Check Logic And Stochastic Flow Recharging Location Model

We first consider a transportation network as shown in figure 3.2 that consists of a single path q, denoted by $\phi(N^q, A^q)$. For each EV_m , the source nodes and sink nodes are added to build an expanded transportation network based on the stochastic simulation of the SoC at the enter and exit node of transportation network. The corresponding distance is consistent with the stochastic distribution introduced in Part A:

$$d_m^q(r,O) = R_O^{EV_m} \tag{3.69}$$

$$d_m^q(D,s) = R_D^{EV_m} \tag{3.70}$$

Accordingly, we could construct the $\phi_m(N^{q,m}, A^{q,m})$ for EV_m on path q by repeat the same procedure of FRLM.

Based on the expanded transportation network, the SFRLM can be formulated mathematically. The objective is to optimally locate FCS to maximize the total flow covered and the corresponding stochastic FRLM can be formulated as follow:

$$Maximization: F = 365 \times \sum_{q \in Q} \sum_{t \in T} \sum_{m \in f_{q,t}^{rr}} (1 - x_{rs}^{q, EV_m})$$
(3.71)

Subject to:

$$\sum_{\{j|(i,j)\in A^{q,m}\}} x_{ij}^{q,EV_m} - \sum_{\{j|(j,i)\in A^{q,m}\}} x_{ji}^{q,EV_m} = \begin{cases} 1 & \text{if } i = r^{q,m} \\ -1 & \text{if } i = s^{q,m} \\ 0 & \text{if } i \neq r^{q,m} s^{q,m} \end{cases} \quad \forall i \in N^{q,m}, q \in Q$$
(3.72)

$$\sum_{\left\{j|(j,i)\in A^{q,m}\right\}} x_{ji}^{q,EV_m} \le \alpha_i^{FCS} \quad \forall i \in N^{q,m}, q \in Q$$
(3.73)

$$x_{ij}^q \ge 0 \quad \forall (i,j) \in A^q, q \in Q \tag{3.74}$$

3.3.3.3 Capacitated FRLM

The service capability of FCS and the EV driving range constraints are jointly incorporated in CFRLM. The EV charging demand can be estimated based on the traffic flow and then the captured EVs and the charging load of FCS can be calculated with the consideration of FCS service capability. The CFRLM is described as follows:

The objective function is to maximize the total captured traffic flow that could be charged by the candidate stations:

Maximization:
$$F = 365 \times \sum_{q \in Q} \sum_{t \in T} f_{q,t}^{rs} (1 - x_{rs}^q)$$
 (3.75)

Accordingly, the traffic flow captured by candidate FCS located at node n in time t can be calculated. This variable is dependent on the number of EVs traffic flow with charging intention and constrained by the capacity of FCS.

Subject to:

$$\sum_{\{j|(i,j)\in A^q\}} x_{ij}^q - \sum_{\{j|(j,i)\in A^q\}} x_{ji}^q = \begin{cases} 1 & \text{if } i = r^q \\ -1 & \text{if } i = s^q \\ 0 & \text{if } i \neq r^q s^q \end{cases} \quad \forall i \in N^q, q \in Q$$
(3.76)

$$\sum_{\{j|(j,i)\in A^q\}} x_{ji}^q \le \alpha_i^{FCS} \quad \forall i \in N^q, q \in Q$$
(3.77)

$$x_{ij}^q \ge 0 \quad \forall (i,j) \in A^q, q \in Q \tag{3.78}$$

$$\sum_{q \in \mathcal{Q}_i} \sum_{\{j \mid (j,i) \in A^q\}} f_{q,i}^{r_s} x_{ji}^q \le Cap_i \quad \forall i \in N^q$$
(3.79)

The service capability Cap_i of FCS at transportation node n is denoted by the number of EVs that can be served during a time step. This variable is determined by the number of charging posts installed in FCS and can be estimated by the queuing theory.

3.3.3.4 Time-Series Capacitated FRLM

The service capability of FCS within a time step should be considered to estimate the captured EVs and the charging load of FCS accurately. For the CFRLM in previous research, the charging demand that beyond the FCS capacity constraints is regarded as the unsatisfied charging demand. However, for long-trip driving EVs in large-scale transportation system, they prefer to wait for the charging service. Therefore, in Time-Series CFRLM, those unsatisfied charging demand is regarded as time-deferred charging demand and calculated in the next time-step. The service capability Cap_n of FCS at transportation node n is denoted by the number of EVs that can be served during a time step and can be estimated by the queuing theory.

The objective function is to maximize the total captured traffic flow that could be charged by the candidate stations:

$$Maximization: F = 365 \times \sum_{i \in N^q} \sum_{t \in T} \lambda_{i,t} \alpha_i^{FCS}$$
(3.80)

The charging demand at FCS located at *i* during each time step can be calculated as follow:

$$CD_{i,t} = \begin{cases} \sum_{q \in Q_i} f_{q,t}^{rs} (1 - x_{rs}^q) & \text{if } CD_{i,t-1} \le Cap_i \\ \sum_{q \in Q_i} f_{q,t}^{rs} (1 - x_{rs}^q) + CD_{i,t-1} - Cap_i & Otherwise \end{cases} \quad \forall i \in N^q$$

$$(3.81)$$

Accordingly, the traffic flow captured by candidate FCS located at node *i* in time *t* can be calculated as follow:

$$\lambda_{i,t} = \begin{cases} CD_{i,t} & \text{if } CD_{i,t} \le Cap_i \\ Cap_i & Otherwise \end{cases} \quad \forall i \in N^q$$
(3.82)

This variable is dependent on the number of EVs traffic flow with charging intention and constrained by the capacity of FCS.

Subject to:

$$\sum_{\{j|(i,j)\in A^{q}\}} x_{ij}^{q} - \sum_{\{j|(j,i)\in A^{q}\}} x_{ji}^{q} = \begin{cases} 1 & \text{if } i = r^{q} \\ -1 & \text{if } i = s^{q} \\ 0 & \text{if } i \neq r^{q} s^{q} \end{cases} \quad \forall i \in N^{q}, q \in Q$$
(3.83)

$$\sum_{\{j|(j,i)\in A^q\}} x_{ji}^q \le \alpha_i^{FCS} \quad \forall i \in N^q, q \in Q$$
(3.84)

$$x_{ii}^q \ge 0 \quad \forall (i,j) \in A^q, q \in Q \tag{3.85}$$

The service capability Cap_i of FCS at transportation node n is denoted by the number of EVs that can be served during a time step. This variable is determined by the number of charging posts installed in FCS and can be estimated by the queuing theory.

Chapter 4 A Stochastic Joint-Planning Framework for Electric-Vehicle Charging System and Distribution Network in Urban Area

4.1 Introduction

With the number of EVs on the road has continued to increase, private and publicly accessible charging infrastructure is in urgent demand at the same time. Appropriate planning arrangements and regulations of EV charging system are needed to facilitate the charging of EVs and defer the re-investment of electricity networks.

The geographical target planning areas of EV charging system can be urban areas and highways. The charging infrastructure planning in urban area [28-29, 46-48, 87, 165-169] is featured with large density of EV penetration, high utilization ratio of charging infrastructure and limited average driving distance. Compared with urban area, the population density and EV penetration rate in rural area are expected to be relatively small. However, the average daily driving range and charging demand in rural areas are comparably large. The highway transportation network generally powered by high voltage distribution network with large service radius and the EV battery capacity shall be considered while select the FCS location. [163, 170-172] explored the planning strategy of charging facilities on highway.

Australia is the most urbanised country on earth: more than 75% of Australians lived in urban areas in 2013. The average distance travelled by a light passenger vehicle in 2014 was 13,800km per year—an average of just 38km per day. For EV charging system in urban areas, the charging infrastructures are divided into two parts: 1) Level 1&2 charging facilities installed at private and public parking lots, e.g. home, residential districts, workplaces and commercial areas as primary charging methods for EV routinely charging; 2) Level 3 fast charging station is a complementary charging method for EV refuelling in case of urgent situation.

The Level 1 & 2 charging facilities supply power to parking EVs, which is node based and therefore the charging demand is calculated based on node load and included in the conventional load profile. The Level 3 FCS mainly provides charging service to the on-route EVs, which couples both transportation and power networks. Therefore, the location and size of FCS in transportation system should meet the driving demand, charging convenience and associate constraints. And the considerations should be given to the EV mobility, dynamic driving behaviours and uncertain charging habits.

Additionally, the rapid increase in Electric Vehicle and different market factors bring challenge to the prediction of the penetration rate of EV number. The estimates of the rate of uptake of EVs for light passenger use vary widely with some scenarios gradual and others aggressive. And there has been much effects on EV penetration rate from incentives, tax breaks and market price.

Given this background, this research work is devoted to addressing a stochastic joint planning framework for both EV charging system and distribution network where the EV behaviours in both transportation network and electrical system are considered. And the planning issue is formulated as a

multi-objective model with both the capital investment cost and service convenience optimized. The optimal planning of EV charging system in urban area is the target geographical planning area in this work where the service radius and driving distance is relatively limited. Compared with existing papers, the major contributions of this work can be summarized as below:

A flexible planning model is proposed, in which the uncertainty of the penetration rate of EVs is incorporated. The Monte-Carlo simulation method is used to evaluate this uncertainty. And a confidence interval is employed to enable the efficiency and effectiveness of this uncertainty analysis.

A dynamic traffic assignment model is incorporated with a flow-capturing location model to evaluate the captured traffic flow based on the optimal planning result. This method can best model the driving behaviours of EVs in urban areas. With the queuing theory and waiting time incorporated, the simulation result indicates a concept planning scheme with the best commercial value, social warfare and service ability.

The probabilistic SOC distribution for on-route EVs is analysed to evaluate the arrival rate of EVs in a FCS p. As the drivers' intention for fast charging service is largely determined by the SOC of the EVs. And we use sigmoid fitting curve in this work to compute the rate of EV approaching the FCS for charging service.

In this work, a multi-objective optimization model is formulated. The captured traffic in the transportation network is used as an indicator of the convenience of travelling and charging service as well as the market potential of the charging station. The total cost is used for cost efficiency analysis including capital investment cost for both charging system and distribution network, operation cost of the system and the loss in distribution network. And the decomposition based multi-objective evolution algorithm (MOEA/D) is employed to solve this multi-objective optimization model and get the optimal pareto frontier. And then different methods can be employed to find the final decision.

A scenario-based charging system model is formulated in section 4.2. Section 4.3 propose the uncertainty analysis method of EV penetration rate. Section 4.4 formulate the multi-objective joint planning model. Section 4.5 introduces the multi-objective evolutionary algorithm (MOEA)/D for problem solving. Case study is described in Section 4.6. And conclusions are draw in Section 4.7.

4.2 Scenario-based EV Charging System Modelling

The Electric Vehicle (EV) charging system models and the charging profiles are described in this section. Due to the unavailability of historical data related to EV driving behaviour and charging demand. A scenarios-based traffic assignment model as summarized in figure 4.1 is employed to model the charging profile, which represents a trade-off between accuracy and the complexity of the planning problem. According to the travelling statistical data, the trip-parking ratios and driving behaviours in transportation network are discretised into a definite number of states. Then the traffic flow on each path in transportation structure can be artificially generated by the User Equilibrium based Traffic Assignment Model (UETAM) and Dijkstra's algorithm is used to find the shortest paths.

The charging system analyzed in this work is for urban area with large density of EV penetration, high utilization ratio of charging infrastructure and limited average driving distance. Accordingly, the charging infrastructures are divided into two parts: Level 1&2 charging facilities installed at home and parking lots

of residential districts, workplaces and commercial areas, etc. is the preferred or general selection for EV routinely charging; Level 3 FCS provides a complementary charging method for EV refueling in urgent situation.



Fig. 4.1 Scenario-based EV Charging Demand Modelling

4.2.1 Traffic Flow Scenario Modelling

In this work, a probabilistic model based on a travelling statistical data [171] is used to generating virtual data of travelling-parking vehicle number to describe the annual driving behaviour. The daily trip-

parking ratio in transportation network is summarized into SN^{TP} scenarios, based on the travelling statistical data, with each scenario assigned by a probability of $prob(SN_s^{TP})$.

Accordingly, for each scenario, the number of parking vehicles at each transport network node in each time step during a day can be obtained as follow:

Average number of EVs parking at distribution node *i* in time *t* is $v_{i,t}^{PR} (SN_s^{TP}) \times X^{EV}$, where X^{EV} is the Electric Vehicle number deployed in planning area and $v_{i,t}^{PR} (SN_s^{TP})$ is the parking rate at node *n* in time step *t* based on scenario SN_s^{TP} .

For each scenario SN^{TP} , the trip ratio of vehicles in each time step during a day can be obtained as well. The number of on-route vehicle in the transportation system can be calculated as follow:

Average number of EVs travelling in transport network in time *t* is $v_t^{TR} (SN_s^{TP}) \times X^{EV}$, where X^{EV} is the Electric Vehicle number in planning area, and $v_t^{TR} (SN_s^{TP})$ represents the trip rate in time step *t* based on scenario SN_s^{TP} .

To generate the traffic flow distribution, a User Equilibrium Traffic Assignment Model proposed in previous studies [141] is adopted in this work. The traffic flow on path $_q$ connecting OD (Origin-Destination) pair rs in time t is denoted by $f_{q,t}^{rs}$ and can be obtained by solving the equilibrium function employed in [47]. In this User Equilibrium Traffic Assignment Model, the Bureau of Public Road (BPR) function is employed to describe the link performance and the Dijkstra Algorithm is used to find the shortest path between two transport nodes. And the obtained traffic flow distribution $f_{q,t}^{rs}$ is subject to:

$$v_t^{TR}\left(SN_s^{TP}\right) \times X^{EV} = \sum_{r \in N^T} \sum_{s \in N^T} \sum_{q \in Q_{rs}} f_{q,t}^{rs}$$

$$(4.1)$$

4.2.2 Charging Demand Modelling of Level 1&2 Charging System

Level 1&2 charging facilities is the primary selection for EV's routinely recharging. Therefore, the facilities will be spread all over urban areas and be accessible at parking lots of residential, workplaces and commercial areas, etc. In this work, the charging demand of Level 1&2 charging facilities is simulated for each distribution nodes and the number of charging facilities at each distribution system node is assumed to be proportional to the number of EVs deployed in the corresponding area. The number of charging facilities deployed at each distribution nodes could be determined by:

$$z_{i}^{CF} = \sum_{t \in T} \left(X^{EV} \times \sum_{s \in SN^{TP}} \left[v_{i,t}^{PR} \left(SN_{s}^{TP} \right) prob\left(SN_{s}^{TP} \right) \right] \right) \times \gamma^{CF} \quad \forall i \in N^{D}$$

$$(4.2)$$

Based on the EV charging rate data, the daily probabilistic profile of the charging rate is obtained and can be denoted by $Rate_i^{EV}$.

Accordingly, the nodal charging demand in each time step could be approximately calculated as:

$$P_{i,t}^{CF} = \begin{cases} v_{i,t}^{PR} \left(SN_s^{TP} \right) \times X^{EV} \times Rate_t^{EV} \times p^{CF} & \text{if } v_{i,t}^{PR} \left(SN_s^{TP} \right) \times X^{EV} \times Rate_t^{EV} \le z_i^{CF} \\ z_i^{CF} p^{CF} & \text{otherwise} \end{cases}$$

$$\forall i \in N^{FCS}, \forall i \in N^{FCS} \end{cases}$$

$$(4.3)$$

4.2.3 Charging Demand Modelling of FCS

FCS provide an important charging method for on-route EVs with urgent charging demand to compensate the relatively short driving range of EVs. And therefore, the drivers' intention for fast charging service and is largely determined by the SOC of the EVs. In this case, the EV arrival rate is estimated based on the captured traffic flow and the probabilistic SOC distribution.

And we use sigmoid fitting curve in this work to compute the rate of EV approaching the FCS for charging service. And the parameters can be specified based on the survey. The distribution of EVs' SoC is determined by normal fitting method based on the central limit theorem in probability theory. And we use the MC simulation to generate the random SoC of EVs driving on the routes.

$$p(SoC^{EV}, \mu^{SoC}, \sigma^{SoC}) = \frac{1}{\sigma^{SoC} \sqrt{2\pi}} \exp\left(-\frac{(\mu^{SoC} - SoC^{EV})^2}{2(\sigma^{SoC})^2}\right)$$
(4.5)

In consideration of the service quality and commercial profits, FCS are generally located on transportation nodes with intensive traffic flow around. And the traffic flow captured by candidate FCS at node n In time t can be calculated by the scenario-based traffic flow model.

$$f_{n,t}^{FCS} = \sum_{r \in N^T} \sum_{s \in N^T} \sum_{q \in Q_{rs}} f_{q,t}^{rs} \delta_{n,q}^{FCS}, \quad \forall t \in T \quad \forall n \in \phi^{FCS}$$
(4.6)

Where,

$$\delta_{n,q}^{FCS} = \begin{cases} 1 & if \text{ node n exist on path q} \\ 0 & Otherwise \end{cases}$$
(4.7)

Accordingly, arrival number of EVs could be defined by,

$$\lambda_{n,t}^{FCS} = \int_{0}^{f_{n,t}^{FCS}} g^{char} (SoC^{EV}) = \int_{0}^{f_{n,t}^{FCS}} \frac{1}{1 + \exp(\beta SoC^{EV})}$$
(4.8)

The average waiting time can largely affect the FCS service quality and is an important consideration for FCS planning. In this work, the number of fast charging facilities is obtained by solving a nonlinear integer programming model constrained by the average waiting hour during rush hour. In this model, the M/M/s queuing theory is used to calculate the average waiting time and the charging sequence is determined by Poisson Process [47, 131]. The M/M/s queuing theory is described as follows:

Objective: *Minimization*: z_n^{FCS} Subject to:

$$W_n^{RH} \le \overline{W} \quad \forall n \in \phi^{FCS}$$
 (4.9)

$$W_{n}^{RH} = \frac{(\lambda_{n}^{RH})^{z_{n}^{FCS}+1}}{(z_{n}^{FCS}-1)!(z_{n}^{FCS}\mu - \lambda_{n}^{RH})\mu^{z_{n}^{FCS}}} \left[\sum_{a=0}^{z_{n}^{FCS}-1} \frac{(\lambda_{n}^{RH})^{a}}{\mu^{a}a!} + \frac{(\lambda_{n}^{RH})^{z_{n}^{FCS}}}{\mu^{z_{n}^{FCS}}(z_{n}^{FCS}!)} \left(\frac{z_{n}^{FCS}\mu}{z_{n}^{FCS}\mu - \lambda_{n}^{RH}} \right) \right]^{-1}$$
(4.10)

The mean arrival number of EVs in the FCS located at node n during the rush hour could be defined by,

$$\lambda_n^{RH} = \int_0^{f_n^{RH}} \frac{1}{1 + \exp\left(\beta SoC^{EV}\right)}$$
(4.11)

$$f_n^{RH} = \max\left\{ f_{n,t}^{FCS} \middle| f_{n,t}^{FCS} = \sum_{r \in N^T} \sum_{s \in N^T} \sum_{q \in \mathcal{Q}_{rs}} f_{q,t}^{rs} \delta_{n,q}^{FCS}, \quad \forall t \in T \right\} \quad \forall n \in \phi^{FCS}$$
(4.12)

Then the fast charging demand profile can be obtained accordingly, based on the obtained optimal size of each FCS and the arrival rate in each time step.

$$P_{i,t}^{FCS} = \begin{cases} n_{i,t} p^{fcs} & \text{if } n_{i,t} \le \mathbf{z}_i \\ P_i^{FCS,\max} & \text{otherwise} \end{cases} \quad \forall i \in N^{FCS}, \forall i \in N^{FCS} \end{cases}$$
(4.13)

$$P_i^{FCS,\max} = \mathbf{z}_i p^{fcs} \quad \forall i \in N^{FCS}$$

$$(4.14)$$

4.3 Weighted K-Means Clustering for FCS Primary Selection

The weighted k-means clustering algorithm can be used to split a given data set with weighing factor into a fixed number (k) of clusters which is decided initially. And the centroid is a data point (imaginary or real) at the center of a cluster.

The K-means clustering algorithm uses iterative refinement to produce a result. The algorithm inputs are the number of clusters K and the data set. The data set is a collection of features for each data point. And in this case, the feature is the coordinate location and the connected traffic flow. The algorithm starts with initial estimates for the K centroids, which can either be randomly generated or randomly selected from the data set.

A weight function

$$w: X \to R^+ \tag{4.15}$$

Defines the weight of every element.

In this case, the weighting factor of the node is dependent on the average number of EVs parking in transport network in time t, which is denoted by

$$w(i) = f\left(v_{i,t}^{PR}\left(SN_{s}^{TP}\right) \times X^{EV}\right)$$
(4.15)

Giving a clustering $\left\{C_1, C_2, \cdots, C_k
ight\}$, the weighted k-means objective function is

$$\sum_{i=1}^{k} \sum_{x \in C_i} w(x) \|x - c_i\|^2$$
(4.15)

Where c_i is the mean of C_i . That is

In this research, the selected candidate site for FCS would be the node that is the most close to C_i .

4.4 Uncertainty Analysis of EV Penetration Rate

The penetration rate of EVs in the future market can be influenced by different factors including the market price of EV, battery technology development, charging infrastructure, and government policy, etc. Market analysis and expert knowledge can be used to give a general estimation of the number of Electric Vehicle deployed at the end of the planning horizon. As the uncertainty from EV number can cause risk to the future charging system, it is essential to take the uncertainty of EVs' penetration rate into account at the planning stage. The growth rate of EVs could be modelled by Gaussian distribution as follows:

$$p(\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(X-\mu)^2}{2\sigma^2}}$$
(4.15)

Where μ refers to the predicted increasing rate of EV, σ is the standard deviation determined by the planning horizon and other uncertain factors. *x* is the increasing rate of EV. The possible scenarios are constructed based on statistical data, and the candidate planning will be applied into each scenario to find the optimal planning that could best compensate the difference in EV growth rates under each scenario. In this research work, a confidence-interval construct the scenarios randomly. The sampling process is constrained by a confidence interval to avoid some extreme cases that is certainly impossible and ensure the accuracy of the simulation.

$$X^{\min} \le X_n \le X^{\max}$$
(4.16)

4.5 Multi-Objective Joint Planning Model

Optimal allocation of Electric Vehicle Charging system include determine the number of charging posts in each distribution node, and the siting and sizing of the Fast Charging Stations in coupled transportation and distribution network. The fast charging stations are collaboratively planned with renewable generation and distribution system. In terms of the convenience of the charging service, the maximization of the total captured traffic flow is considered as one of the objective. This joint planning strategy can minimize the investment cost and network reinforcement cost while satisfy the distribution network constrains and charging demand.

Electricity network and charging system need to ensure system adequacy, quality of service and efficient investment. The extent to which the EV charging demand will impact electricity networks will depend highly on the shares of EVs, technologies and charging modes used. The EV penetration rate and charging profile can be analyzed based on the methods proposed in section 4.2 and 4.3, then the charging system is collaboratively planned with the distribution system. Accordingly, a multi-objective joint planning model is developed to achieve trade-off between cost and adequacy.

4.5.1 Minimization of Overall cost on Investment and Energy Loss

For EV charging system planning, the location and size of charging facilities are the main concerns, Ans in this joint planning of distribution and EV charging system, the construction of charging facilities, and the construction or reinforcement of feeders and substations are regarded as the possible solutions to bear the future charging demand. Accordingly, the total investment cost, operation cost, energy losses and waiting time are major concerns in this planning issue.

The joint planning model is formulated as a mixed-integer, nonlinear programming problem and subjects to associated constraints, as described in follows.

Objective:

$$Minimization: F(X) = \sum_{n=1}^{N} \frac{C(n)}{(1+r)^{n}}$$

$$C(n) = C_{DS}(n) + C_{CS}(n) + C_{L}(n)$$
(4.17)

The objective function in (1) is the gross investment cost, loss cost and waiting-time cost of multi-stage planning project. $C_{DS}(n), C_{CS}(n), C_L(n)$ indicate the cost of distribution system, EV charging stations, power loss and charging waiting time on stage n.

The investment cost for distribution system includes the cost for distribution lines C_{DL} and substations C_{ss} and can be calculated as follow:

$$C_{DS} = C_{DL} + C_{SS} = \sum_{ij \in \phi^{DL}} \sum_{a \in \phi^a} c_a^{DL} x_{ij,a} l_{ij} + (\sum_{i \in \phi^{S_1}} \sum_{b \in \phi^b} c_b^{S_1} y_{i,b}^{S_1} + \sum_{i \in \phi^{S_2}} \sum_{c \in \phi^c} c_c^{S_2} y_{i,c}^{S_2})$$
(4.18)

The investment cost for FCS can be calculated as follow:

$$C_{CS} = \sum_{n \in \phi^{FCS}} \alpha_n^{FCS} \left(c^{FCS} z_n^{FCS} + c_n^{Land} z_n^{FCS} + c^{FCSOther} \right)$$
(4.19)

The cost of energy losses during each planning stage can be calculated as follow:

$$C_{L} = \sum_{Y=1}^{Y_{\text{Stage}}} \left\{ 365 \times c^{E} \sum_{ij \in \phi^{DL}} \sum_{a \in \phi^{a}} \sum_{t \in T} [g_{ij,a} x_{ij,a} (U_{i,t}^{2} + U_{j,t}^{2} - 2U_{i,t} U_{j,t} \cos \theta_{ij,t})] \right\}$$
(4.20)

The capital recovery factor can be calculated by,

$$d^{DL,S,FCS,DG} = \frac{\varepsilon(1+\varepsilon)^{Y^{DL,S,FCS,DG}}}{(1+\varepsilon)^{Y^{DL,S,FCS,DG}} - 1}$$
(4.21)

 $Y^{DL}, Y^{S}, Y^{FCS}, Y^{DG}$ is lifespan of distribution line, substation, fast charging station and distribution generation. And ε denotes interest rate.

Constraints:

Power flow equation constraints:

$$P_{i,t}^{S} = P_{i,t}^{L} + (P_{i,t}^{CP} + \sum_{n \in \phi^{i}} P_{n,t}^{FCS}) + U_{i,t} \sum_{j \in N^{D}} U_{j,t} (G_{ij} x_{ij,a} \cos \theta_{ij,t} + B_{ij} x_{ij,a} \sin \theta_{ij,t}) \forall i \in N^{D}, \forall t \in T'$$
(4.22)

$$Q_{i,t}^{s} = Q_{i,t}^{L} + U_{i,t} \sum_{j \in N^{D}} U_{j,t} (G_{ij} x_{ij,a} \sin \theta_{ij,t} - B_{ij} x_{ij,a} \cos \theta_{ij,t}) \forall i \in N^{D}, \forall t \in T'$$

$$(4.23)$$

Capacity constraints for substation:

$$(P_{i,t}^{s})^{2} + (Q_{i,t}^{s})^{2} \le (\overline{S_{i}^{0}})^{2} \forall i \in \phi^{s0}, \forall t \in T'$$
(4.24)

$$(P_{i,t}^{S})^{2} + (Q_{i,t}^{S})^{2} \le (\overline{S_{i}^{0}} + \sum_{b \in \phi^{b}} y_{i,b}^{S1} \overline{S_{i,b}^{S1}})^{2} \quad \forall i \in \phi^{S1}, \ \forall t \in T'$$
(4.25)

$$(P_{i,t}^{S})^{2} + (Q_{i,t}^{S})^{2} \le (\sum_{c \in \phi^{c}} y_{i,c}^{S2} \overline{S_{i,c}^{S2}})^{2} \quad \forall i \in \phi^{S2}, \ \forall t \in T'$$
(4.26)

Capacity constraints of Fast Charging Station:

$$z^{\min} \le z_n \le z^{\max} \quad \forall n \in \phi^{FCS}$$
(4.27)

Where $z^{\min} z^{\max}$ are size limits of Fast Charging Station. Apparent power constraints:

$$P_{ij,a,t}^2 + Q_{ij,a,t}^2 \le (x_{ij,a}\overline{S_{ij,a}})^2 \quad \forall ij \in \phi^{DL}, \ \forall t \in T'$$

$$(4.28)$$

$$P_{ij,a,t} = x_{ij,a} [U_{i,t}^2 g_{ij,a} - U_{i,t} U_{j,t} (g_{ij,a} \cos \theta_{ij,t} + b_{ij,a} \sin \theta_{ij,t})] \forall ij \in \phi^{DL}, \forall t \in T'$$
(4.29)

$$Q_{ij,a,t} = x_{ij,a} \left[-U_{i,t}^2 \mathbf{b}_{ij,a} - U_{i,t} U_{j,t} (g_{ij,a} \sin \theta_{ij,t} - b_{ij,a} \cos \theta_{ij,t}) \right] \forall ij \in \phi^{DL}, \forall t \in T'$$
(4.30)

Bus voltage limit constraints:

$$U_i^{\min} \le U_{i,t} \le U_i^{\max} \quad \forall i \in N^D, \forall i \in T'$$
(4.31)

DS radiation topology constraints are modelled as below based on graph theory [203]:

$$\sum_{ij \in \phi^{DL}} \sum_{a \in \phi^a} x_{ij,a} = n^{DS} - n^S$$
(4.32)

Other rational constraints:

$$\sum_{a \in \phi^a} x_{ij,a} \le 1 \quad \forall ij \in \phi^{DL}$$
(4.33)

$$\sum_{b \in \phi^b} y_{i,b}^{S1} \leq 1 \quad \forall i \in \phi^{S1}$$
(4.34)

$$\sum_{c \in \phi^c} y_{i,c}^{S2} \le 1 \quad \forall i \in \phi^{S2}$$
(4.35)

4.5.2 Maximization of the Captured Traffic Flow

To improve the EV charging infrastructure investment efficiency, the second optimization objective is to maximize the captured traffic flow. In this work, the annual captured traffic flow by FCSs is maximized by solving the probabilistic FCLM.

The key aspect of this model is that the driver will deviate from the pre-determined path to recharge their vehicles at the nearest FCS if the SoC of EV battery lower than the threshold. With the increasing use of on-board vehicle navigation systems, it is reasonable to assume that drivers could take the shortest or least cost path to their target recharging stations and then to their destination. This model could better reflect the driving behaviour of EVs when the FCS network is sparse and can better evaluate the effects on distribution network from the charging load of FCS.

The objective function is to maximize the total captured traffic flow that could be charged by the candidate recharging stations. The first part evaluates the number of EVs that receive charging service on predetermined route and the second part calculate the total number of EVs that will reselect the route for charging service.

Objective Function:

$$Maximization: F = \sum_{Y=1}^{Y_{stage}} \left\{ 365 \times \left[\sum_{r \in N^T} \sum_{s \in N^T} \sum_{q \in \mathcal{Q}_{rs}} \left(\tau_q^{rs} \times g_q^{char} \times \sum_{t \in T} f_{q,t}^{rs} \right) + \sum_{r \in N^T} \sum_{s \in N^T} \sum_{q \in \mathcal{Q}_{rs}} \left((1 - \tau_q^{rs}) \times g_q^{dev} \times \sum_{t \in T} f_{q,t}^{rs} \right) \right] \right\}$$
(4.36)

Accordingly, the traffic flow captured by candidate fast charging station in time t can be calculated by:

$$f_{n,t}^{FCS} = \sum_{r \in N^T} \sum_{s \in N^T} \sum_{q \in \mathcal{Q}_{rs}} f_{q,t}^{rs} g_q^{char} \delta_{n,q}^{FCS} \alpha_n^{FCS} + \sum_{r \in N^T} \sum_{s \in N^T} \sum_{q \in \mathcal{Q}_{rs}} f_{q,t}^{rs} g_{qd}^{dev} \delta_{n,qd}^{FCS} \alpha_n^{FCS}$$
(4.37)

Subject to:

the traffic flow on path q connecting the OD pair rs can be captured only if at least one Fast Charging Station exists on path q.

$$\tau_q^{rs} = \begin{cases} 1 & \text{if FCS exists on path } q \\ 0 & \text{if no FCS exists on path } q \end{cases}$$
(4.38)

$$\delta_{n,q}^{FCS} = \begin{cases} 1 & if \text{ the node n FCS exists on path q } (n \in \phi_q^{Node}) \\ 0 & Otherwise \end{cases}$$
(4.39)

$$\delta_{n,qd}^{FCS} = \begin{cases} 1 & \text{if the node n FCS exists on the deviation path qd} (n \in \phi_{qd}^{Node}) \\ 0 & Otherwise \end{cases}$$
(4.40)

$$\sum_{n \in \phi_q^{FCS}} \alpha_n^{FCS} \ge \tau_q^{rs}$$
(4.41)

4.6 Solving Method

The problem in this section is formulated as a multi-stage, multi-objective and mixed integer nonlinear programming model. In this case, a decomposition based multi-objective evolutionary algorithm (MOEA)/D is introduced and employed to find Pareto optimal solutions. This Pareto optimality theory can define trade-off solutions and the decision-makers could select one from them according to the specific needs.

The major steps for solving the multi-objective joint-panning model with MOEA/D is shown below, and detailed introduction on MOEA/D can be found in [174].



Fig. 4.2 The MOEA/D Optimization Process

The final decision is made based on the specific needs and selected from the non-dominated solutions on Pareto Front. Many final decision-making methods have been proposed to make this decision [175].

4.7 Case Studies and Discussions

An integrated 54-node distribution and 25-node transportation systems are employed to simulate the proposed joint-planning method and obtain the numeric optimal planning result. The test systems are

indicated in APPEDIX A. In this case, the optimization is completed in three steps. First, a k-means clustering algorithm is employed to select the candidate location for FCS based on the traffic flow information. Secondly, the multi-objective optimization is achieved by using MOEA/D and the non-dominated solutions and the approximated Pareto-front are obtained. Finally, the optimal solution is decided based on the final decision-making strategies.

A. Test System Description

A 15 KV, 54-node distribution system is utilized to simulate the urban electricity network and demonstrate the effectiveness of the joint optimization model. This 54-node system constitutes four substations (two existing substations and two candidate substations) and 61 feeders (17 existing feeders and 44 candidate feeders). The topology of this distribution system could be found in [202]. The normal load levels at the end of each planning stage are integrated into the simulation and are nor detailed described here. The reinforcement and investment costs on distribution network are summarized in table 4.1.

The 25-node transportation system [147] is used to simulate the transportation metropolitan area. The correlation between the transportation and distribution system is reasonably assumed and described in figure 4.4.

It is assumed that the planning area is a fast-developing urban area with increasing population, emerging new load and system expansion demand. The planning horizon considered here is 15 years and three stages. The number of vehicles per family is assumed to be 1.59 based on the NSW household travel survey [203]. The average daily charging frequency is 0.4 which is estimated based on the average daily trip in [203]. And the prediction of household number, EV penetration rate and confidence-interval constraints are listed in table 4.2 for uncertainty analysis. As the charging demand from EV drivers is largely determined by the SoC state, therefore the parameters setting for probabilistic SOC distribution are also listed in table 4.2.

Substation		S1		S2		S3		S4		
		Туре		T2	T1	T2	T1	T2	T1	T2
Substations		Initial Capacity (MVA)		16.7		5.7	-		-	
C	l	Reinforcement (MVA)	13.3	16.7	13.3	16.7	-	-	-	-
		Construction (MVA)	-	-	-	-	16.7	22.2	16.7	22.2
	Rein	einforcement Cost (10 ⁶ US\$)		10	8	10	-	-	-	-
	Cor	nstruction Cost (10 ⁶ US\$)	-	-	-	-	14	20	16	24
FCS Fac		acility Cost (10 ⁴ US\$) 4.7								
C C	Site Cost (10⁴ US\$)		Location Dependent (30-40)							
C _{CS}		Other Cost (10⁴ US\$)	4							
Cable	Cable and Construction		2							
c_a^{DL} (10 ⁴ US\$/100m)		3								
Electricity Price		270 US\$/MWh								
Interest Rate		7%								

 TABLE 4-1
 Capital Cost on Distribution and Charging System

	Predicted Increasing Rate μ_{yr}	$\mu_{0-5} = 70\%$ $\mu_{5-10} = 50\%$ $\mu_{10-15} = 30\%$
	Standard Deviation σ	1
		$X_{0-5}^{\min} = 10\%$
EV Penetration	Minimum Increasing Rate <i>x</i> ^{min}	$X_{5-10}^{\min} = 10\%$
		$X_{10-15}^{\min} = 5\%$
		$\mu_{0-5} = 200\%$
	Maximum Increasing Rate x ^{max}	$\mu_{5-10} = 200\%$
		$\mu_{10-15} = 200\%$
Battery SoC	Medium SoC $\mu^{\scriptscriptstyle SoC}$	70%
	Standard Deviation $\sigma^{\scriptscriptstyle SoC}$	$\sqrt{0.5}$

TABLE 4-2 EV Penetration Uncertainty and SoC Probabilistic Parameters

And based on the weighted k-means clustering method, the centroids selected as candidate sites for FCS panning are indicated in Table 4.3.

TABLE 4-3	Candidate Site for FCS Planning
-----------	---------------------------------

Candidate FCS	1	2	3	4	5	6	7	8	9	10	11	12
Location in DS	2	4	6	9	12	16	28	30	35	38	46	48
Location in Transport	5	7	12	4	14	3	16	8	11	13	19	17

B. The Optimal Planning Scheme

The non-dominated solutions and the approximate Pareto Frontier is obtained as shown in figure 4.3. The decision maker could make a trade-off between these two objectives and make the final decision accordingly.



Fig. 4.3 Non-dominated solutions and the approximated Pareto frontier

C. Final-decided Planning Scheme

In this case, one non-dominated result is selected as the final-decided planning scheme. The details of the two-stage joint planning topology are summarized in table 4-4.

Stage 1	2 5 7			8 9 12				
(0 – 5 yr)	4 (7)	12 (14)	28(16)	30(8)	35(11)	48(17)		
Stage 2		3		11				
(5 – 10 yr)		6 (12)		46 (19)				
Stage 3	1							
(10 – 15 yr)	2 (5)							

· · · · · · · · · · · · · · · · · · ·

TABLE 4-5Summary of the selected Planning Topology

Objective	Investment and Energy Cost	Captured traffic Flow
Values	$5.08{ imes}10^7$ USD	$6.71{ imes}10^8$ USD

4.8 Conclusion

In this research work, a multi-stage multi-objective joint planning model is developed for integrated EV charging system and distribution network planning. In this model, the uncertainties in EV charging system planning is fully explored and a probabilistic FCLM is proposed to simulate the on-route charging demand. In this research work, the traffic flow pattern is analysed based on UETAM. However, the FCS planning scheme may affect the traffic flow distribution. And therefor, further considerations like traffic congestion, traffic flow re-distribution and emergency control can be explored in the future work.

Chapter 5 Joint Planning of EV Charging System and Renewable Generation in Urban Distribution System and Transportation Network

5.1 Introduction

The energy system expects a major transformation due to the continuing embrace of renewable generation and transport electrification and new energy-efficient technologies. This diversification may impose uncertainty and risk to the power industry and further intensify the technical, financial and environmental challenges faced by the power system.

The large integration of intermittent PV with limited controllability and predictability can bring voltage rises, increased power losses, power fluctuation and reverse power flows to the distribution system [176]. On the other hand, the distribution system also has potential risk of excessive voltage drops, increased network losses and feeder overloads caused by the future penetration of EVs. Therefore, considerations should be given to the joint planning and coordinated operation of DG and EV charging system in electricity network.

By far, the optimal planning strategies of distributed generation (DG) in power system have been studied by many researchers [177-178]. The limited controllability and predictability of renewable generation are considered in [177]. In this joint planning framework, DG can bring the following benefits: 1) Reduce cost of upgrades: DG units can relieve congestion in network feeders and defer previously required system upgrades, thus reducing the NPV of the required upgrades. 2) Reduce cost of energy losses: Installing DG units can alleviate the increasing system loss from the growing extra load imposed by EVs [66-67, 76].

Many research works are now working towards the integration of DG in EV charging infrastructure. [87] studied the economic benefit of integrating PV generation with fast-charging stations. [88-90] focus on the coordinated control strategies of PV integrated charging station. [88-89] demonstrates that coordinated PEV charging could improve distributed PV power integration significantly. [90] shows that coordinated PEV charging could alleviate voltage rise problems caused by PV power injection. The BSS can be used to accommodate PV generation in [54].

Joint Planning of EV charging stations and renewable power generation has been analysed in []. [91] studied joint planning of on-site PV generation and BSS with the capacities of PV panels, EV batteries, and EV chargers optimized. [92] proposed a multi-stage multi-objective planning algorithm for uncoordinated EV charging facilities and renewable generation at parking lots. [93] developed a multi-objective model to optimize the siting and sizing of charging stations and distributed renewable generation. [94] designed a EV parking lots at workplace powered by PV generation with V2G technology. [95] studied the sizing of a EV charging station powered by commercial grid-integrated PV systems. [96] proposed a two-stage approach to simultaneously allocating EV charging stations with distributed renewable resources in distribution systems.

5.2 Probabilistic Based System Modelling

The renewable generation, EV charging demand and normal load modelling with the integration of relevant uncertainties are described in this section. The models are built based on the following assumptions:

- The models are built for metropolitan planning purpose, where the utilization ratio of EV is much higher, the average daily driving distance is relatively limited and the mainly installed DG is PV.
- The DG units operate at a fixed power factor, which is assumed to be unity for the purposes of this work.
- The PV generation, load profile and EV charging demand are discretised into a definite number of states, which represents a trade-off between accuracy and the complexity of the planning problem.

5.2.1 DG Modelling

In this section, the PV generation modelling is described and the relevant uncertainties are also analysed. The probabilistic solar irradiance model proposed in [179-180] is employed in this wok for PV generation modelling. The stochastic variations of the solar irradiance indicated by solar forecast errors are assumed to follow the Beta distribution. In this case, a day is divided into 24 time-steps, each of which is one hour and has 20 solar irradiance states with a step of 0.05 kW/m². Accordingly, the Beta probability density function for solar irradiance during each hour is modelled based on the historical data [181]. The historical data is used to generate the mean and deviation of the hourly solar irradiance of the day.

Over each period, the Beta PDF [74] for solar irradiance *s* can be expressed as follows:

$$f_b(s) = \begin{cases} \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} s^{(\alpha - 1)} (1 - s)^{(\beta - 1)}, & 0 \le s \le 1, \ \alpha, \beta \ge 0\\ 0, & \text{otherwise} \end{cases}$$
(5.1)

Where, $f_b(s)$ is the Beta distribution function of s - the random variable of solar irradiance (kW / m^2). α and β are parameters of $f_b(s)$, which are calculated using the mean (α) and standard deviation (β) of solar irradiance s as follows:

$$\beta = (1 - \mu)(\frac{\mu(1 + \mu)}{\sigma^2} - 1)$$
(5.2)

$$\alpha = \frac{\mu \times \beta}{1 - \mu} \tag{5.3}$$

The probability of the solar irradiance state *s* during any specific hour can be calculated from Beta distribution as follows:

$$\rho(s) = \int_{s_1}^{s_2} f_b(s) ds$$
(5.4)

Where s_1 and s_2 are solar irradiance limits of state s.

This PDF can be obtained by defining the solar irradiance PDF for each time steps throughout a day. Based on the historical data [181], the mean and standard deviation of the solar irradiance in each time step of the day is calculated. It is assumed that each hour has 20 states for solar irradiance with a step of 0.05 kW/m². From the calculated mean and standard deviation, the PDF with 20 states for solar irradiance is generated for each time step of the day, and the probability of each solar irradiance state is determined. Accordingly, the PV generation of the corresponding time step is obtained [179].

The maximum output power from the PV module at solar irradiance *s* can be expressed as follows [77]:

$$P_i^{PV_0}(s) = N_i^{PV} \times FF \times V_v \times I_v$$
(5.5)

And the *FF*, V_v , I_v can be obtained as follows:

$$FF = \frac{V_{MPP} \times I_{MPP}}{V_{oc} \times I_{sc}}$$
(5.6)

$$V_{y} = V_{oc} - K_{v} \times T_{cy} \tag{5.7}$$

$$I_{y} = s[I_{sc} + K_{i} \times (T_{cy} - 25)]$$
(5.8)

$$T_{cy} = T_A + s(\frac{N_{OT} - 20}{0.8})$$
(5.9)

Where, N_i^{PV} is the number of PV modules at node $i \cdot T_{cy}$ and T_A are the average cell and ambient temperatures (${}^{o}C$). K_i and K_v are current and voltage temperature coefficients ($A / {}^{o}C$ and $V / {}^{o}C$). N_{OT} is nominal operating temperature of cell in ${}^{o}C \cdot FF$ is fill factor. V_{oc} and I_{sc} are the open-circuit voltage and short circuit current. V_{MPP} and I_{MPP} are voltage and current at maximum point

The expected output power at solar irradiance *s* is calculated as

$$P_i^{PV}(s) = P_i^{PV_0}(s)\rho(s)$$
(5.10)

The total expected output power $P_{PV}(t)$ (average output power) of a PV module across any specific period t can be obtained as follows [77]:

$$P_{i,t}^{PV} = \int_0^1 P_i^{PV_0} \rho(s) ds$$
(5.11)

The capacity factor of a PV module (CF_{PV}) can be defined as the average output power (P_{PV}^{avg}) divided by the rated power or maximum output (P_{PV}^{max}):

$$CF_{PV} = \frac{P_{PV}^{avg}}{P_{PV}^{max}}$$
(5.12)

The average output power is calculated using $P_{PV}(t) = \int_0^1 P_{PV_0}(s)\rho(s)ds$ for each hour based on historical data.

5.2.2 Traffic Date Based EV Charging System Modelling

The charging system in urban area can be dived into Level1&2 charging facilities and fast charging stations. The Level 1&2 charging facilities are widely installed at homes and park lots of residential, business and commercial areas, etc. These charging facilities are the primary daily charging method for EVs and generally provide charging service to the parked EVs. Additionally, FCS are generally located at transportation route and can be regarded as a complementary charging method for EVs. And FCS generally provide fast charging service to on-route EVs.

Accordingly, the charging load from Level 1&2 charging facilities and FCS shall be analysed based on the EVs distribution in urban area and the traffic flow in transportation network respectively. A data based modelling method is employed in this work to simulate the travelling and charging behaviour of EVs. The statistical travelling data [173] is used to generate the travelling-parking vehicle number and describe the annual driving behaviour.

The number of parking vehicles at each transport network node in each time step during a day can be obtained as follow:

Average number of EVs parking at distribution node *i* in time $t = v_{i,t}^{PR} \times X^{EV}$, where X^{EV} is the Electric Vehicle number deployed in planning area and $v_{i,t}^{PR}$ is the parking rate at node *n* in time step *t* based on the historical data.

The trip ratio of vehicles in each time step during a day can be obtained as well. The number of on-route vehicle in the transportation system in time t can be calculated as $v_t^{TR} \times X^{EV}$, where X^{EV} is the Electric Vehicle number in planning area, and v_t^{TR} represents the trip rate in time step t based on scenario SN_s^{TP} . Based on the trip rate, a User Equilibrium Traffic Assignment Model proposed in previous studies [141] is adopted in this work to generate the traffic flow. The traffic flow on path q connecting OD (Origin-Destination) pair rs in time t is denoted by $f_{q,t}^{rs}$ and is obtained by solving the BPR based User Equilibrium Traffic Assignment Model, the Dijkstra Algorithm is used to find the shortest path between two transport nodes. And the obtained traffic flow distribution $f_{q,t}^{rs}$ is subject to:

$$v_t^{TR} \times X^{EV} = \sum_{r \in N^T} \sum_{s \in N^T} \sum_{q \in \mathcal{Q}_{rs}} f_{q,t}^{rs}$$
(5.13)

For charging demand modelling of level 1&2 charging system, the charging load is estimated based on the statistical travelling data including both the parked EV and traffic flow. In this work, the number of charging facilities at each distribution system node is assumed to be proportional to the number of EVs deployed in the corresponding area. And the charging demand of Level 1&2 charging facilities at each distribution nodes is estimated accordingly.

The number of charging facilities deployed at each distribution nodes could be determined by:

$$z_i^{CF} = \sum_{t \in T} \left(X^{EV} \times v_{i,t}^{PR} \right) \times \gamma^{CF} \quad \forall i \in N^D$$
(5.14)

The average EV charging frequency can be calculated based on the average daily driving distance. Accordingly, a time varying charging rate denoted by $Rate_t^{EV}$ is proposed to describe the probability of a parked car under charging in each time step.

Accordingly, the nodal charging demand in each time step could be approximately calculated as:

$$P_{i,t}^{CF} = \begin{cases} v_{i,t}^{PR} \times X^{EV} \times Rate_t^{EV} \times p^{CF} & \text{if } v_{i,t}^{PR} \times X^{EV} \times Rate_t^{EV} \le z_i^{CF} \\ z_i^{CF} p^{CF} & \text{otherwise} \end{cases} \quad \forall i \in N^{FCS}, \ \forall i \in N^{FCS} \end{cases}$$
(5.15)

For charging demand modelling of FCS charging station, the charging load at FCS is estimated based on the EV arrival rate which depends on the captured traffic flow and time-varying charging rate in each time step. In this work, a time varying fast charging rate denoted by $Rate_t^{FC}$ is proposed to describe the probability of on-route EV arriving for charging in each time step. In consideration of the service quality and commercial profits, FCS are generally located on transportation nodes with intensive traffic flow around. And the traffic flow captured by candidate FCS at node n In time t can be calculated by the scenario-based traffic flow model.

$$f_{n,t}^{FCS} = \sum_{r \in N^T} \sum_{s \in N^T} \sum_{q \in Q_r} f_{q,t}^{rs} \delta_{n,q}^{FCS}, \quad \forall t \in T \quad \forall n \in \phi^{FCS}$$
(5.16)

Where,

$$\delta_{n,q}^{FCS} = \begin{cases} 1 & if \text{ node n exist on path q} \\ 0 & Otherwise \end{cases}$$
(5.17)

Accordingly, arrival number of EVs could be defined by,

$$\lambda_{n,t}^{FCS} = f_{n,t}^{FCS} \times Rate_t^{FC}$$
(5.18)

Then the fast charging demand profile can be obtained accordingly, based on the optimal size of each FCS and the arrival rate in each time step.

$$P_{i,t}^{FCS} = \begin{cases} \lambda_{n,t}^{FCS} p^{fcs} & \text{if } \lambda_{n,t}^{FCS} \leq \mathbf{Z}_i \\ \mathbf{Z}_i p^{fcs} & \text{otherwise} \end{cases}, \quad \forall i \in N^{FCS}, \forall i \in N^{FCS} \end{cases}$$
(5.19)

5.2.3 Load Model

The fluctuation renewable energy along with the charging station alters the demand profile. The net demand can be represented as,

$$P_{i,t} = P_{i,t}^{L} - P_{i,t}^{PV} + P_{i,t}^{FCS} + P_{i,t}^{CF}$$
(5.20)

5.3 Formulation of the Joint-Planning Model

The joint-planning model consider the investment and operation cost on Charging system, distribution network and renewable generation. The collaborative planning model is formulated as a mixed-integer, nonlinear programming problem.

In this part, the multi-objective function constitutes the minimization of the overall cost of investment, operation and energy losses, as well as maximisation of the captured traffic flow.

Objective 1: Minimize the overall investment cost and energy losses

The first objective function is developed to attain an optimal distribution network and substation, EV charging station as well as renewable generation planning scheme for the planning horizon with the investment and operation costs minimized and technical constraints respected:

$$Minimization: F_1 = C_{DS} + C_{CS} + C_{DG} + C_L$$
(5.21)

The objective function represents the gross investment cost of joint planning project and the cost on power loss. C_{DS} , C_{CS} , C_{DG} indicate the annual investment cost of distribution system, EV charging station and distributed generation. C_L Represents the annual cost of energy losses.

The annual cost for distribution system includes the annual cost for distribution lines C_{DL} and substations C_s and can be calculated by,

$$C_{DS} = C_{DL} + C_{S} = d^{DL} \sum_{ij \in \phi^{DL}} \sum_{a \in \phi^{a}} c^{DL}_{ij,a} x_{ij,a} l_{ij} + d^{S} (\sum_{i \in \phi^{S}} \sum_{b \in \phi^{b}} c^{S1}_{i,b} y^{S1}_{i,b} + \sum_{i \in \phi^{S2}} \sum_{c \in \phi^{c}} c^{S2}_{i,c} y^{S2}_{i,c})$$
(5.22)

The annual cost for Fast Charging Station can be calculated by,

$$C_{CS} = d^{FCS} \sum_{n \in \phi^{FCS}} \alpha_n^{FCS} \left(c^{FCS} z_n^{FCS} + c_n^{Land} z_n^{FCS} + c^{FCSOther} \right)$$
(5.23)

The annual cost for distributed generation can be calculated by,

$$C_{DG} = d^{DG} \sum_{i \in \phi^{DG}} \beta_i^{DG} (c^{DG} k_i^{DG} + c^{DGOther})$$
(5.24)

The annual cost of energy losses can be calculated by,

$$C_{L} = 365 \times c^{E} \sum_{ij \in \phi^{DL}} \sum_{a \in \phi^{a}} \sum_{t \in T} [g_{ij,a} x_{ij,a} (U_{i,t}^{2} + U_{j,t}^{2} - 2U_{i,t} U_{j,t} \cos \theta_{ij,t})]$$
(5.25)

The capital recovery factor can be calculated by,

$$d^{DL,S,FCS,DG} = \frac{\varepsilon(1+\varepsilon)^{Y^{DL,S,FCS,DG}}}{(1+\varepsilon)^{Y^{DL,S,FCS,DG}} - 1}$$
(5.26)

Where, Y^{DL} , Y^{S} , Y^{FCS} , Y^{DG} Corresponding lifespan of distribution line, substation, fast charging station and distribution generation. And ε represents the Interest rate.

The constraints of this optimization model are listed as below:

Power flow equation constraints:

The power generated at each bus is dependent on the type of DG and the connected capacity at the bus. The power demand at each bus is the sum of the normal load, EV charging demand at each bus and possible FCS charging demand. It is assumed that both the PV generation and EV charging operate at a unity power factor.

$$P_{i,t}^{S} + P_{i,t}^{DG} = P_{i,t}^{L} + (P_{i,t}^{CP} + \sum_{n \in A_{t}} P_{n,t}^{FCS}) + U_{i,t} \sum_{j \in N^{D}} U_{j,t} (G_{ij} \cos \theta_{ij,t} + B_{ij} \sin \theta_{ij,t}) \forall i \in N^{D}, \forall t \in T'$$
(5.27)

$$Q_{i,t}^{S} = Q_{i,t}^{L} + U_{i,t} \sum_{j \in N^{D}} U_{j,t} (G_{ij} \sin \theta_{ij,t} - B_{ij} \cos \theta_{ij,t}) \forall i \in N^{D}, \forall t \in T'$$
(5.28)

Capacity constraints for substation:

$$(P_{i,t}^{S})^{2} + (Q_{i,t}^{S})^{2} \le (\overline{S_{i}^{0}})^{2} \forall i \in \phi^{S0}, \forall t \in T'$$
(5.29)

$$(P_{i,t}^{S})^{2} + (Q_{i,t}^{S})^{2} \le (\overline{S_{i}^{0}} + \sum_{b \in \phi^{b}} y_{i,b}^{S1} \overline{S_{i,b}^{S1}})^{2} \quad \forall i \in \phi^{S1}, \ \forall t \in T'$$
(5.30)

$$(P_{i,t}^{s})^{2} + (Q_{i,t}^{s})^{2} \le (\sum_{c \in \phi^{c}} y_{i,c}^{s2} \overline{S_{i,c}^{s2}})^{2} \quad \forall i \in \phi^{s2}, \ \forall t \in T'$$
(5.31)

Capacity constraints of Fast Charging Station:

$$z^{\min} \le z_n \le z^{\max} \quad \forall n \in \phi^{FCS}$$
(5.32)

Where z^{\min} and z^{\max} are the size limits of Fast Charging Station.

Upper and Lower Limits of distributed generation:

$$P_i^{DG\min} \le P_{i,t}^{DG} \le P_i^{DG\max} \quad \forall i \in N^D \forall t \in T'$$
(5.33)

Where $P_i^{DG\min}$ indicates the power generation limit of DG at node *i*

Capacity constraints of distributed generation:

The DG output power at a certain bus is zero without DG placement and update to the installed capacity after placement. Many countries have introduced polices to achieve renewable targets. And the target PV generation rate is a% in this planning model. The maximum bus connection constraint: the maximum capacity of the DG connection to any individual bus is limited based on the voltage level and on the technical constraints of the distribution system.

$$\sum_{i \in N^D} P_{i,t}^{DG} \le P^{DG\max} \quad \forall t \in T$$
(5.34)

$$(1-a\%)\sum_{t\in T}\sum_{i\in N^{D}} P_{i,t}^{S} \le a\% \times \sum_{t\in T}\sum_{i\in N^{D}} P_{i,t}^{DG}$$
(5.35)

It is expected that the renewable generation could at least supply 10% of the total demand.

For power system modelling, the apparent power bus voltage and other constraints were modelled in equation 4.28 - 4.35.

Objective 2: Maximization of the Captured Traffic Flow

To improve the EV charging infrastructure investment efficiency, the second optimization objective is to make FCSs serve as many EVs as possible. Therefore, the annual captured traffic flow by FCSs is maximized by solving the flow-capturing location model.

$$\max f_2 = \sum_{r \in N^T} \sum_{s \in N^T} \sum_{q \in \mathcal{Q}_{rs}} T_{q,annual}^{rs} \tau_q^{rs}$$
(5.36)

Subject to:

The traffic flow on path connecting the origin and destination (OD) pair *rs* can be captured only if at least one FCS exists on path *q*.

$$\sum_{k\in\Omega_q^K} u_k \ge \tau_q^{rs}$$
(5.37)

 $T_{q,annual}^{rs}$, which represents the annual traffic flow on path connecting OD pair *rs*, is given as follow:

$$T_{q,annual}^{rs} = d^{annual} \sum_{t \in T} f_{q,t}^{rs}$$
(5.38)

Where the binary variable τ_q^{rs} denotes whether the traffic flow on path q can be captured., $f_{q,t}^{rs}$ is the traffic flow on path q connecting OD pair rs in t.

5.4 Case Studies

An integrated 54-node distribution and 25-node transportation systems are employed to simulate the proposed joint-planning method and obtain the numeric optimal planning result. In this case, the optimization is completed in three steps. First, a k-means clustering algorithm is employed to select the candidate location for FCS based on the traffic flow information. Secondly, the multi-objective optimization is achieved by using MOEA/D and the non-dominated solutions and the approximated Pareto-front are obtained. Finally, the optimal solution is decided based on the final decision-making strategies.

A. Test System Description
A 15 KV, 54-node distribution system is utilized to simulate the urban electricity network and demonstrate the effectiveness of the joint optimization model. The corresponding candidate route of this distribution system could be found in [202]. The normal load levels at the end of each planning stage are integrated into the simulation and are nor detailed described here. The reinforcement and investment costs on distribution network are summarized in table 5.1. The 25-node transportation system [147] is used to simulate the transportation metropolitan area. The correlation between the transportation and distribution system is reasonably assumed.

The number of vehicles per family is assumed to be 1.59 based on the NSW household travel survey [203]. The average daily charging frequency is 0.4 which is estimated based on the average daily trip in [203].

		Substation	S	1	S	2	S	3	S4	
		Туре	T1	T2	T1	T2	T1	T2	T1	T2
Substations		Initial Capacity (MVA)	16.7		16.7		-		-	
C		Reinforcement (MVA)	13.3	16.7	13.3	16.7	-	-	-	-
C_{SS}		Construction (MVA)	-	-	-	-	16.7	22.2	16.7	22.2
	Rein	forcement Cost (10 ⁶ US\$)	8	10	8	10	-	-	-	-
	Construction Cost (10 ⁶ US\$)		-	-	-	-	14	20	16	24
ECS	FCSFacility Cost (10^4 US\$) C_{cs} Site Cost (10^4 US\$)Other Cost (10^4 US\$)		4.7							
FCS			Location Dependent (30-40)							
C_{CS}			4							
PV	Par	nel Cost (Per Watt) (US\$)	4							
C_{DG}	Other Cost (Per Watt) (US\$)		2							
Cable c_{z}^{DL}	Cable and Construction (10 ⁴ US\$/100m)		3							
Electricity Price			270 US\$/MWh							
Interest Rate				79	%					

TABLE 5-1 Capital Cost on Distribution and Charging System

All the distribution nodes can be selected as the candidate site for PV installation. According to the weighted k-means clustering method, the centroids selected as candidate sites for FCS panning are indicated in Table 5.2.

TABLE 5-2 EV Penetration Uncertainty and SoC Probabilistic Parameters

Candidate FCS	1	2	3	4	5	6	7	8	9	10	11	12
Location in DS	2	4	6	9	12	16	28	30	35	38	46	48
Location in Transport	5	7	12	4	14	3	16	8	11	13	19	17

B. The Optimal Planning Scheme

The non-dominated solutions and the approximate Pareto Frontier is obtained as shown in figure 5.1. The decision maker could make a trade-off between these two objectives and make the final decision accordingly.



Fig. 5.1 Non-dominated solutions and the approximated Pareto frontier

In this case, one non-dominated result is selected as the final-decided planning scheme. The details of the two-stage joint planning topology are summarized in table 4-4 and table 4-5.

TABLE 5-3	Multi-stage FCS Planning Topology
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ECS	ECS 2		7	8	9)	12
FC3	4 (7)	12 (14)	28(16)	30(8)	35(11)	48(17)
	4		12	30			48
PV	300 kW		600 kW	600 kW	/		1000 kW

TABLE 5-4Summary of the selected Planning Topology

Objective	Investment and Energy Cost	Captured traffic Flow
Values	1.27×10^{7}	7.50×10^{7}

5.5 Conclusion

This research work develops a planning scheme integrated both the future charging facilities and renewable generation in power system planning. Due to the inaccessible of reliable EV driving and charging data, the modelling may not accurate or complex. However, it is reasonable at this stage to deal with the facility planning issue. The work in this area will be enhanced with the availability of data that indicates charging characteristics and user habits, information that will not be available prior to significant EV penetration level.

Chapter 6 An Energy Management System of Smart Building with Electric Vehicle, Photovoltaic and Battery Energy Storage

6.1 Background and Introduction

The electricity grids are undergoing inevitable transition towards Smart Grid architecture. And the deployment of photovoltaic (PV), battery energy storage (BES), Electric Vehicle (EV) and smart meter on residential and commercial level is increasing. Utilizing smart technologies for energy management within home and building is gaining greater attraction. The emerging technology - Smart Building Energy Management System (EMS) play an important role in achieving Demand Side Management (DSM) and further Smart Grid [182-183]. And the development of this technology is driven by the environment problem, the intermittency issue of renewable distributed generation (DG), government policy and economic considerations.

Levels of renewable DG has been increasing significantly in Australia due to the developing technology and the government incentives. And the BES is considered as a technology to compensate the surpluses power and intermittency of renewable energy generation. Additionally, the accelerated growth of EV market is expected to lead a rapid growth of EV penetration over the next few years. On the other hand, the current distribution network topology allows the bidirectional energy flow and the customers could feed-in the surpluses energy to the grid [183]. This bidirectional interaction between suppliers and consumers allows all market participators to be more flexible and controllable in their operational strategies of electricity usage.

For consumer side, Smart Home/Building EMS has emerged that allows the demand side to become an active player in the power systems [184-186]. The EMS is integrated into residential houses or commercial buildings where renewable DG, BES, EV charging facilities and energy-efficient appliances are implemented, along with smart meter, cloud platform and control systems, to reduce its overall energy consumption and peak demand [187]. Furthermore, this technology can benefit the electricity grid, reduce carbon footprint and minimize the energy expenses without comprising the modern lifestyle.

The study of supplying EV charging demand by grid-connected PV panels at workplace parking areas has been conducted in many recent research works [188–193]. This technology aims to bring multiple technical and economic benefits to vehicle, garage owners and power utilities and the optimal charging algorithms are proposed to achieve economic benefits, reduce the curtailment of surplus PV generation, minimize voltage deviation and enhance the self-consumption of PV generation. [188] designs a charging station with PV panels to maximize the consumption of PV power while minimizing voltage deviations in distribution networks, where a real-time fuzzy logic controller that incorporates a probabilistic model was proposed to forecast PV generation and EV charging loads. This real-time controlling method is also employed to control multiple charging stations in power networks to minimize charging cost, network power losses and voltage deviations [189]. In [190], an optimal EV

charging algorithm based on forecasted PV generation and load demand is proposed to minimize the power cost in commercial buildings. [191] developed a heuristic operation approach that accommodate EV charging facilities and PV panels to enhance the self-consumption of PV generation in commercial buildings. In [192], a PV integrated charging station was proposed to reduce the intermittency of PV generation and the electricity cost in the charging station. In [193], an operation model is developed for a PV-EV parking deck to minimize the effect from the intermittency of PV generation and maximize the total revenue of the parking deck. In this model, the parking deck is operated as a micro-grid.

The EMS proposed in [194] utilizes a Mixed-Integer Liner Programming (MILP) approach to generate the optimal operational schedule of the energy resources and appliances within a building. This model allows the consumers to minimize their electricity consumption from the grid, reduce the costs and maintain a comfort level of living. [195] evaluate a two-stage stochastic optimization framework for EMS integrated PV-storage system to identify the benefits based on a longer decision horizon. [196] compare the method of heuristic scenario reduction technique integrated stochastic MILP and the dynamic programming approach in solving smart home EMS. [197] presents an approximate dynamic programming (APD) approach with temporal difference learning for implementing a computationally efficient Home EMS. [198] presents a computationally efficient smart home EMS using an ADP approach with temporal difference leargy resources. The project in [199] integrates thermal inertia in demand response through smart home EMS. [200] manage the distributed energy resources and appliances within a general residential house based on real time pricing scheme. The objectives of the system in [201] is to create a smooth consumption pattern by shift the demand away from peak time and investigate the effects of thermal inertia within the mode.

This research work presents a multi-stage operational planning model of the commercial building EMS with PV, BES and EV charging facilities integrated. The purpose of this model is to optimize the electricity use, accommodate future EV charging demand and reduce the cost on both investment and operation. This optimization is to the owners' benefits based on the current electricity market tariff. The PV generation is assumed to be available to the system in advance in practical, which can be estimated by cloud platform according to the weather and sunlight intensity prediction to achieve real-time, stochastic energy management. In this work, a stochastic scenario-based solar generation model is employed for simulation. On the other hand, the probabilistic EV arrival rate and the uncertainty in EV charging behavior is analyzed in this work to estimate the charging demand. The economic performance of the system with the optimized PV and battery size is also analyzed.

This project focus on two objectives. The first objective is to build a Building EMS including a gridconnected PV system, BES system and EV charging facilities using the MILP methodology to optimize the scheduling and coordination of PV generation, battery charging and EV charging. The second objective is to further optimize the size of PV and battery system based on the proposed EMS to achieve the most economic benefits for building owner. This research work is organized as follows: section 6.2 describe the proposed EMS model and section 6.3 presents the optimization model. Section 6.4 introduce the performance of the system based on a case study of a typical commercial building. The system developed is verified to be functioning as required. Furthermore, the performance of system under different scenarios are analyzed and the most optimized result is achieved.

6.2 System Modelling

Each element within a Commercial Building EMS is modelled individually. The constraints of the system and the corresponding operational characteristics of each component are fully defined in mathematical formulations. The EMS of the building in this work is described in figure 6.1, that consists of a rooftop PV system, battery storage system, electricity grid and the load. Based on the model of each energy block, we could build the optimized model of the EMS operation process under different scenarios.



Fig. 6.1 Overview of the components in Building EMS

6.2.1 Time Horizon and Time Step

The system operation and scheduling is modeled in discrete time. The decision horizon is defined as T and is divided into N time steps with each time step of t_{step} . And n is a variable indicating a specific time step.

$$N = \frac{T}{t_{step}}$$
(6.1)

$$1 \le n \le N \tag{6.2}$$

6.2.2 Grid-Connected PV System

The rooftop PV system is designed as delivering uncontrollable electricity generation based on the solar insulation and installed system size. The power generation of the PV system is uncertain and stochastic which is defined by variable $P_{PV}(n)$ in each time step during the operation horizon.

The probabilistic PV generation model is employed in this work for electricity generation modelling. Beta probability distribution function (PDF) closely match the random characteristic of solar irradiance. Over each time step, the Beta PDF for solar irradiance s can be expressed as follows:

$$f_b(s) = \begin{cases} \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} s^{(\alpha - 1)} (1 - s)^{(\beta - 1)}, & 0 \le s \le 1, \ \alpha, \beta \ge 0\\ 0, & \text{otherwise} \end{cases}$$
(6.3)

Where, $f_b(s)$ is the Beta distribution function of s. And s is the random variable of solar irradiance (kW / m^2). α and β are parameters of $f_b(s)$, which are calculated using the mean (α) and standard deviation (β) of solar irradiance s as follows:

$$\beta = (1 - \mu)(\frac{\mu(1 + \mu)}{\sigma^2} - 1)$$
(6.4)

$$\alpha = \frac{\mu \times \beta}{1 - \mu} \tag{6.5}$$

The historical hourly-averaged solar irradiance data is divided into 96 groups and further differentiate based on seasons. And the Beta distribution function for each group is obtained accordingly. The renewable data at hour t, season s are generated from the corresponding fitting function $f_b(t,s)$ and randomly. The maximum output power from the PV module at solar irradiance s can be expressed as follows:

$$P_{PV}(s) = N_v^{PV} P^{Panel} \times FF \times V_v \times I_v$$
(6.6)

Where,

$$FF = \frac{V_{MPP} \times I_{MPP}}{V_{oc} \times I_{sc}}$$
(6.7)

$$V_y = V_{oc} - K_v \times T_{cy} \tag{6.8}$$

$$I_{y} = s[I_{sc} + K_{i} \times (T_{cy} - 25)]$$
(6.9)

$$T_{cy} = T_A + s(\frac{N_{OT} - 20}{0.8})$$
(6.10)

Where,

 N_y^{PV} is the number of PV panel with power of $P^{Panel}(W)$ installed at the year of y; T_{cy} and T_A are the average cell and ambient temperatures (°C); K_i and K_v are current and voltage temperature coefficients (A / °C and V / °C); N_{OT} is nominal operating temperature of cell in °C, FF is fill factor; V_{oc} and I_{sc} are the open-circuit voltage and short circuit current; V_{MPP} and I_{MPP} are voltage and current at maximum point.

The operation mode of the power generated by PV panel will be controlled using a binary integer variable $PV_m(n)$. When $PV_m(n)$ is zero, the power from PV will supply to the building ($P_{PV_build}(n)$), either supply to BES ($P_{PV_build}(n)$) with conversion efficiency factor f_{DC_DC} or to the system load (

 $P_{PV_load}(n)$ with conversion efficiency factor f_{DC_AC} . When $PV_m(n)$ is one, the power will feed the electricity grid ($P_{PV_grid}(n)$) after the converting process with an efficiency factor (f_{DC_AC}). Accordingly, it can be concluded that:

$$P_{pv_{grid}}\left(n\right) = f_{DC_{AC}}PV_{m}\left(n\right)P_{pv}\left(n\right)$$
(6.11)

$$P_{pv_build}\left(n\right) = \left(1 - PV_m\left(n\right)\right)P_{pv}(n)$$
(6.12)

6.2.3 The Electricity Grid

The electricity grid in this project is modelled as an infinite bus with high ratings relatively which means that all the electricity demand in this model could be supplied by the electricity grid and can accommodate the maximum generation from rooftop PV system. To reflect this, the upper constraint (L_{p_srid}) for the power flow feed into grid ($P_{s_sin}(n)$) and power flow obtained from grid ($P_{s_sout}(n)$) can be assigned a reasonable value that is large enough to accommodate the electricity consumption and PV generation. In addition, $S_{grid}(n)$ is indicate the state of the electricity grid. When $S_{grid}(n)$ is one, the grid is supplying power to the system. When $S_{grid}(n)$ is zero, the power from building feed-into the grid. This is implemented based on the constraints (4.7) and (4.8):

$$0 \le P_{g_{out}}\left(n\right) \le L_{p_{out}}S_{grid}\left(n\right)$$
(6.13)

$$0 \le P_{g_{s_{in}}}\left(n\right) \le L_{p_{g_{rid}}}\left(1 - S_{g_{rid}}\left(n\right)\right)$$
(6.14)

The power from grid $P_{g_{out}}(n)$ can be used to supply the load in system ($P_{g_{out}}(n)$), charge the BES ($P_{g_{out}}(n)$) or charge the connected EVs ($P_{g_{out}}(n)$). And the power feed-into the grid $P_{g_{out}}(n)$ may from the PV generation $P_{PV_{out}}(n)$, the BES discharging $P_{b_{out}}(n)$ or the connected EVs $P_{cs_{out}}(n)$. Accordingly, the power of the grid at time step n in this system can be calculated as follows:

$$P_{G}(n) = P_{g_{a}in}(n) - P_{g_{a}out}(n)$$
(6.15)

If $P_g(n) > 0$, the system is consuming power from grid, if $P_g(n) < 0$, the power from system is feeding into the grid and if $P_g(n) = 0$, no power flow into or from grid.

6.2.4 Battery Storage System

The BES can be regarded as a buffer of energy in the EMS that could store the surpluses PV generation, supply the peak demand and achieve the potential economic benefits. In this research work, the battery is defined by the size (B_{size}), the maximum depth of discharge (DOD) (B_{depth}), the charging rate range (B_{rate}^{min} , B_{rate}^{max}) and the efficiency factor (B_{eff}) for charging and conversion process which is assumed to be constant. The state of charge (SOC) of the BES is defined by $B_{soc}(n)$.

A binary integer ($S_{battery}^{idle}(n)$) is introduced to indicate the state of battery, either IDLE or operating mode. In this modelling, 0 indicated the operating mode and 1 indicates the IDLE state. Under the operating mode, a binary integer ($S_{battery}(n)$) is introduced to indicate the state of battery, either charging or discharging. In this modelling, 0 indicates the state of charging and 1 indicates the state of discharging. In addition, the variables $P_{b_{cha}}(n)$ and $P_{b_{discha}}(n)$ is the amount of power charging to and discharging from the battery. The behavior of battery is defined by constraints (4.9) and (4.10):

$$B_{rate}^{\min} S_{battery}^{opt} \left(n\right) \left(1 - S_{battery}^{idle}\left(n\right)\right) \le P_{b_discha}\left(n\right) \le B_{rate}^{\max} S_{battery}^{opt}\left(n\right) \left(1 - S_{battery}^{idle}\left(n\right)\right)$$
(6.16)

$$B_{rate}^{\min}\left(1-S_{battery}^{opt}\left(n\right)\right)\left(1-S_{battery}^{idle}\left(n\right)\right) \le P_{b_{cha}}\left(n\right) \le B_{rate}^{\max}\left(1-S_{battery}^{opt}\left(n\right)\right)\left(1-S_{battery}^{idle}\left(n\right)\right)$$
(6.17)

The SOC of the battery $B_{soc}(n)$ is supposed to be tracked throughout the time horizon. In practical, the SOC of current time-step $B_{soc}(n)$ is determined by the SOC of previous time-step $B_{soc}(n-1)$ and the state of the battery $S_{battery}(n-1)$. To achieve the continuity of the modelling, the battery SOC of time-step prior to the initial time step in the optimization horizon is regarded as the value of the final time-step. This BES features and the upper and lower bounds are defined in constraints (4.12-4.14):

$$B_{SOC}(1) = B_{SOC}(N) - t_{step} P_{b_discha}(N) + t_{step} P_{b_cha}(N)$$
(6.18)

$$B_{SOC}(n) = B_{SOC}(n-1) - t_{step} P_{b_{-}discha}(n-1) + t_{step} P_{b_{-}cha}(n-1), \quad n > 1$$
(6.19)

$$B_{depth} \le B_{soc}\left(n\right) \le B_{size} \tag{6.20}$$

Accordingly, the power of the BES at time step n in the building can be calculated as follows:

$$P_B(n) = \frac{1}{B_{eff}} P_{b_cha}(n) - B_{eff} P_{b_discha}(n)$$
(6.21)

If $P_B(n) > 0$, the BES is under charging state, if $P_B(n) < 0$, the BES is under discharging state and if $P_B(n) = 0$ the BES is under IDLE state.

6.2.5 Electric Vehicle and Charging Facilities

The EV in this modelling can be regarded as a load with charging demand and a BES with Vehicle to Grid (V2G) function. However, compared with the BES, the SOC of EVs is stochastic which is determined by the uncertainty in arrival rate of EVs and the probabilistic in SOC of the connected EVs. The number of EV charging facilities installed in the commercial building in the planning horizon is indicated by M and m is the serial number of the *m*th charging port. Where,

$$1 \le m \le M \tag{6.22}$$

In this work, the scenarios SN^{EV} of the EV arriving and leaving during a day at each planning stage are generated based on the field experiment datasheet. In this work, SN^{EV} scenarios are generated by K-

means clustering method. The probabilistic of the scenario sn^{EV} can be described as $p(sn^{EV})$. The sum of the probability of all the possible scenario at any time step is unity as follow:

$$\sum_{1}^{SN^{EV}} p(sn^{EV}) = 1$$
 (6.23)

For each EV charging facility m, the EV arriving and leaving scenario SN^{EV} are modelled as follow:

$$sn^{EV}(m): \left[\left(n_a^m(1), n_l^m(1) \right) \left(n_a^m(2), n_l^m(2) \right) \cdots \left(n_a^m(k), n_l^m(k) \right) \cdots \left(n_a^m(K), n_l^m(K) \right) \right]$$

where,

$$1 \le k \le K \tag{6.24}$$

$$n_l^m(k-1) \le n_a^m(k)$$
 and $n_l^m(0) = 1$ (6.25)

The EV can be regarded as a buffer of energy in the EMS that could store the surpluses PV generation, supply the peak demand and achieve the potential economic benefits. In this research work, the battery is defined by the size ($^{EV_{size}}$), the maximum depth of discharge (DOD) ($^{EV_{depth}}$), the charging and discharging rate ($^{EV_{rate}}$, $^{EV_{rate}}$) and the efficiency factor ($^{EV_{eff}}$) for charging and conversion process which is assumed to be constant. The state of charge (SOC) of the EV is defined by $^{EV_{soc}}(n)$.

A binary integer $\binom{S_m^{idle}(n)}{m}$ is introduced to indicate the state of charging facility m and the connected EV, either IDLE or operating mode. And the binary integer $\binom{S_m^{opt}(n)}{m}$ is introduced accordingly to indicate the state of operating charging facility m and the connected EV, either charging or discharging. In this modelling, 0 indicates the state of charging and 1 indicates the state of discharging.

In addition, the variables $P_m^{EV_cha}(n)$ and $P_m^{EV_discha}(n)$ is the charging facility (*m*) and the connected EV charging and discharging power. The behavior of charging facility (*m*) and the connected EV is defined by constraints (4.21) and (4.22):

$$EV_{rate}^{\min}S_m^{opt}\left(n\right)\left(1-S_m^{idle}\left(n\right)\right) \le P_m^{EV_discha}\left(n\right) \le EV_{rate}^{\max}S_m^{opt}\left(n\right)\left(1-S_m^{idle}\left(n\right)\right)$$
(6.26)

$$EV_{rate}^{\min}\left(1-S_{m}^{opt}\left(n\right)\right)\left(1-S_{m}^{idle}\left(n\right)\right) \leq P_{m}^{EV-cha}\left(n\right) \leq EV_{rate}^{\max}\left(1-S_{m}^{opt}\left(n\right)\right)\left(1-S_{m}^{idle}\left(n\right)\right)$$
(6.27)

Accordingly, for each scenario $sn^{EV}(m)$ of EV arriving and leaving at CF (m), the discharging and charging power of m is constrained by follows:

$$\begin{cases} S_m^{idle}(n) = 1\\ P_m^{EV_ccha}(n) = 0 & \text{if } n_l^m(k-1) \le n < n_a^m(k)\\ P_m^{EV_discha}(n) = 0 \end{cases}$$
(6.28)

The SOC of the connected EV $EV_m^{SOC}(n)$ at CF m is supposed to be tracked as well throughout the connecting duration. In practical, the SOC of current time-step $EV_m^{SOC}(n)$ is determined by the SOC of previous time-step $EV_m^{SOC}(n-1)$, the state of the CF m ($S_m^{idle}(n-1)$, $S_m^{opt}(n-1)$). To achieve the continuity of the modelling, the EV SOC of time-step prior to the initial time step in the optimization horizon is regarded as the value of the final time-step. This feature and the upper and lower bounds are defined in constraints (4.12-4.14):

$$EV_{m}^{SOC}\left(1\right) = EV_{m}^{SOC}\left(N\right) - t_{step}P_{m}^{EV_discha}\left(N\right) + t_{step}P_{m}^{EV_cha}\left(N\right)$$
(6.29)

$$EV_{m}^{SOC}(n) = EV_{m}^{SOC}(n-1) - t_{step}P_{m}^{EV_{-}discha}(n-1) + t_{step}P_{m}^{EV_{-}cha}(n-1), \quad n > 1$$
(6.30)

$$EV_{depth} \le EV_m^{SOC}\left(n\right) \le EV_{size} \tag{6.31}$$

Accordingly, for each scenario $sn^{EV}(m)$ of EV arriving and leaving at CF (m), the SOC of the connected EV $EV_m^{SOC}(n)$ at CF m is constrained by follows:

$$\begin{cases} EV_m^{SOC}(n) = 0, & \text{if } n_l^m(k-1) \le n < n_a^m(k) \\ EV_m^{SOC}(n) : PDF, & \text{if } n = n_a^m(k) \end{cases}$$

$$(6.32)$$

The distribution of EVs' SoC is determined by normal fitting method based on the central limit theorem in probability theory. And we use the MC simulation to generate the random SoC of arriving EVs $EV_m^{SOC}(n_a^m(k))$ that connect to the charging facilities at time step $n_a^m(k)$.

$$p(EV_{SOC}, \mu_{EV}^{SoC}, \sigma_{EV}^{SoC}) = \frac{1}{\sigma_{EV}^{SoC} \sqrt{2\pi}} \exp\left(-\frac{(\mu_{EV}^{SoC} - EV_{SOC})^2}{2(\sigma_{EV}^{SoC})^2}\right)$$
(6.33)

The charging and discharging of every EV needs to guarantee the minimum energy requirement for every EV's next travelling. Therefore, a benchmark of EV SOC ($^{EV_{soc}^{min}}$) is defined in this work which indicate EV could only be charged if the corresponding SOC is lower than the minimum benchmark.

$$\begin{cases} S_m^{idle}(n) = 0\\ S_m^{opt} = 0 & \text{if } EV_m^{SOC}(n) < EV_{soc}^{\min}\\ P_m^{EV_-discha}(n) = 0 \end{cases}$$
(6.34)

This requirement is implemented in constraints (4.29) below:

$$EV_{soc}^{\max}(1 - S_m^{idle}(n))(1 - S_m^{opt}(n)) \ge EV_{soc}^{\min} - EV_m^{SOC}(n)$$
(6.35)

Accordingly, the power of the EV charging system at time step n in the building can be calculated as follows:

$$P_{CS}(n) = \sum_{m=1}^{M} \frac{1}{EV_{eff}} P_m^{EV_cha}(n) - EV_{eff} P_m^{EV_discha}(n)$$
(6.36)

If $P_{CS}(n) > 0$, the system supplies power to EV charging system, if $P_{CS}(n) < 0$, the EV charging system feeds the power into the system and if $P_{CS}(n) = 0$ no power generates from or consume by EV charging system.

6.2.6 Electricity Demand

In this work, the loads are diverted into two parts. One is traditional commercial building load which is simulated as integral electrical demand with the data scaled from the traditional electricity consumption record. We use $P_{load}(n)$ to represent the load for each time step. The other part is the load from EV charging demand which is detailed discussed in 6.2.5 separately. In practice, the electricity demand could be determined by a real-time monitoring system, cloud-based prediction and the direct control signal from control center.

6.2.7 The Balance Equation

The balanced equation (4.31) describes the balance of power flow in this system. The corresponding equation is established with each component of the power system being involved:

$$P_{pv}(n) + P_{G}(n) = P_{B}(n) + P_{CS}(n) + P_{load}(n)$$
(6.37)

6.3 The Optimization Function

In terms of the EMS operation optimization, the objective can be determined by business owner based

on different criteria, such as energy costs, energy consumption, CO_2 emissions, peak demand and user convenience etc. In this work, the objective of EMS function is to minimize the operation cost on system energy consumption considering the benefits from providing charging service. Accordingly, the planning of the system is optimized with the objective as minimization of the total cost including capital investment cost and the total operation cost throughout the planning horizon.

6.3.1 Cost-benefit Analysis: Minimize the System Operation Cost

For this work, the objective of EMS operation is to achieve the most economic benefit for business owner by minimizing the energy cost. And the operation system is thus pricing incentive with the time-of -use (TOU) electricity tariff, dynamic feed-in tariff and pricing scheme for both the charging service and V2G agreement considered. Therefore, the optimization function here is to minimize the operation cost on electricity and formulated as a MILP formulation as shown in (4.32).

Minimization:

$$F_{d}^{Op} = \sum_{n=1}^{N} \left\{ \begin{bmatrix} t_{step} C_{ele}(n) P_{g_{out}}(n) - t_{step} C_{fit}(n) P_{g_{oin}}(n) \end{bmatrix} + \begin{bmatrix} t_{step} C_{v2g}(n) \sum_{m=1}^{M} P_{m}^{EV_{odischa}}(n) - t_{step} C_{cha}(n) \sum_{m=1}^{M} P_{m}^{EV_{ocha}}(n) \end{bmatrix} \right\}$$
(6.38)

Considering the uncertainty in EV arriving-leaving behaviors, a scenario-based stochastic MILP formulation if the problem is described by:

$$F_{d}^{Op} = \sum_{n=1}^{N} \begin{cases} \left[t_{step} C_{ele}(n) P_{g_{out}}(n) - t_{step} C_{fit}(n) P_{g_{out}}(n) \right] + \\ \left[t_{step} C_{v2g}(n) \sum_{m=1}^{M} P_{m}^{EV_{out}}(n) - t_{step} C_{cha}(n) \sum_{m=1}^{M} P_{m}^{EV_{out}}(n) \right] \end{cases}$$

$$Minimization : \sum_{sn^{EV}=1}^{SN^{EV}} prob_{sn^{EV}} F_{d}^{Op}(sn^{EV})$$

$$(6.39)$$

6.3.2 Cost-benefit Analysis: Minimize the total planning and operation cost of the system

To generate the optimal planning scheme, both the capital investment cost and the operation cost are considered when we analysis the economic potential of the project. Therefore, in this work, the net present value (NPV) of the total cost is minimized to achieve the most economic potential of EMS throughout the entire planning horizon (Y).

Minimization:
$$NPV = \sum_{y=1}^{Y} \frac{C_y^{Total}}{(1 + discount)^{y-1}}$$
 (6.40)

In the EMS planning, the total cost includes the capital investment cost (C_v^{In}) and operation cost (C_v^{Op}):

$$C_{y}^{Total} = C_{y}^{In} + C_{y}^{Op}$$
(6.41)

The investment cost includes the cost on PV system, BES and EV charging facilities.

$$C_{y}^{In} = C_{y}^{PV} + C_{y}^{B} + C_{y}^{CF}$$
(6.42)

where C_y^{PV} , C_y^B and C_y^{CF} are the capital cost on PV panels, BES and charging facilities at the year when they are installed. Those cost includes module purchase, installation and relevant accessories. The possible subsidy from government is considered when evaluating the price.

The operation costs include the EMS operation cost optimized in section 4.3.1 and the maintenance cost (C_v^M) every year, which can be calculated as

$$C_{y}^{Op} = \sum_{d=1}^{365} F_{d}^{Op} + C_{y}^{M}$$
(6.43)

This optimization subject to the following constraints:

The number of PV panel N_y^{PV} that could be installed on the rooftop should be smaller than the maximum size. This maximum number N_{max}^{PV} is determined by the rooftop area and the local optimal tilt angle.

$$\sum_{y=1}^{Y} N_{y}^{PV} \le N_{\max}^{PV}$$
(6.44)

The optional number of CF and size of the battery for planning in this work are all determined based on the regular resident population, predicted EV penetration rate and the budget for capital investment.

6.4 Solving Method

In this work, a Mixed Integer Linear Programming (MILP) approach is used to optimize the operation scheduling of EMS. And the modelling can adapt to different situations, with the following advantages: flexible objective function and adjustable system elements.

MILP approach is widely used in deterministic EMS optimization. The objective is modelled as a linear function subject to linear constraints and the variables are continuous or integer. All the operation features are formulated and linearized. Additionally, uncertainty in parameters can be analyzed by a scenario-based stochastic formulation.

Generally, the formulation of the model is composed by control, decision and state variables of all the elements in the system. Accordingly, the matrices of decision and state variables for all the elements can be expressed as follow:

$$X = \begin{bmatrix} x_1^1 & \cdots & x_1^{element} \\ \vdots & \ddots & \vdots \\ x_T^1 & \cdots & x_T^{element} \end{bmatrix} \text{ and } S = \begin{bmatrix} s_1^1 & \cdots & s_1^{element} \\ \vdots & \ddots & \vdots \\ s_T^1 & \cdots & s_T^{element} \end{bmatrix}$$
(6.45)

And then a scenario-based stochastic MILP formulation of the problem can be described by:

$$Minimization: \sum_{sn=1}^{SN} prob(sn) f(X,S)$$
(6.46)

Subject to: $x_t^{element}$ and $s_t^{element}$ satisfy all elements' and user's constraints.

In this work, the MILP optimization function is solved in MOSEK, which could be implanted into MATLAB directly. MOSEK is a software package for the solution of linear, mixed-integer linear, quadratic, mixed-integer quadratic constraint, and conic and convex nonlinear mathematical optimization problems. [11]

6.5 Case Studies

The proposed method was tested on the building of J03 in the University of Sydney. Based on the electricity demand, stochastic EV charging demand and PV & Battery planning scheme, the operation

scheme of EMS is obtained. The results evaluate the benefits of the planning system and verify the effectiveness of the proposed operation method.

Electricity demand is scaled based on the consumption file from smart meter in J03 Building during the year of 2012. The hourly radiation data of PV system come from Daily Global Solar Exposure Climate Data. The geographical location is defined based on the practical location of J03 building. And then the output power can be calculated accordingly, the process is detailed explained in [11]. The simulation parameter is summarized in Table 6.1 – Table 6.3.

Site Location				
Country	AUSTRALIA			
Region & City	NSW, SYDNEY			
Latitude & Longitude	-33.85957, +151.20406			
Time Zone	$\Delta T_{GMT} = GMT + 10:00$			
Altitude	39m			
Available Area	1100 <i>m</i> ²			

TABLE 6-1	Geographical Location and PV System Parameters

TARIE 6-2	TOLI Tariff and Feed-in Tariff

Time	Retail Price (cents/kWh)		
Peak	50		
Shoulder	25		
Off Peak	15		
Feed-in Tariff	10		
Service Charge (cents/day/connect point)	1	65	
Drice Crowth Date	Now - 2020	7.5%	
Price Growth Rate	2020 -	2%	

TABLE 6-3 PV and Battery Storage System Planning Scheme

PV Array					
DV/ Field Orientation	Tilt Angle	30°			
PV FIEld Unentation	Azimuth Angle	-18°			
	Total No 400	In Series:	20 modules		
Module Size	10tal No. – 400	In parallel:	20 strings		
	Area	65	55 m²		
Power Output	100kWp				
	Inverter				
Charactoristics	Op. Voltage	450-820V			
Characteristics	Nom. Power	100kW AC			
PV System					
Produced Energy 182.6 MWh/year			r		
Specific Prod.	1217 kWh/kWp/year				

Perform Ratio (PR)	75.0%
Conversion Efficiency	90%
	PV Cost
Rebate	7%
Tilt Frame Fee	10%
Life Cycle	20
	Battery Cost
Subsidy	10%
Size	1000kWh
Cost	\$700 - \$800 / kWh

The electricity demand for a typical commercial building is summarized in Fig 6.3. It include the electricity consumption scenarios for a year.



Fig. 6.2 Overview of the Electricity Demand Scaling

It is assumed that 6 EV charging ports will be installed in this commercial building in this research. Accordingly, the simulated scenarios of the EV number parking at the building are indicated in Fig. 6.4. And the battery SOC based EV charging demand are summarized in Fig. 6.5.



Fig. 6.3 EV Arrival Rate Scenarios



Fig. 6.4 EV Charging Port Demand Scenarios

The PV & Battery system performance is summarized in Fig. 6.6. As can be seen, a significant amount of power could be supplied by the power from Rooftop PV system. In addition, the reliance of power supply from grid is transferred to off-peak hour with the peak demand is compensated by the power from battery. This verify the advantage of the EMS designed.



Fig. 6.5 Simulation Result of EMS of EMS Operation

6.6 Conclusion

In this research work, an operational planning scheme of PV & battery & EV charging facility system is optimized and the EMS scheme for the system is introduced accordingly. As indicated in the simulation, the operational scheme can coordinate the PV generation, battery charging/discharging, EV charging and other load.

For future study, the system could be extended to suit the future prospective condition, i.e. the widely development of electrical vehicles charging post in commercial building car park. Moreover, we could extend battery life by 'balancing' them, drawing on batteries as individual units, which could enable to make full use of the battery.

A larger number of scenarios should improve the solutions generated by better incorporating the stochastic variables, but this imposes greater computational burden. In this case, techniques, such as heuristic scenario reduction, can be employed to obtain a scenario setoff size, which can be solved within a given time with reasonable accuracy.

Chapter 7 Conclusion and Future Work

In this research work, a multi-stage multi-objective joint planning model is developed for integrated EV charging system and distribution network planning. In this model, the uncertainties in EV charging system planning is fully explored and a probabilistic FCLM is proposed to simulate the on-route charging demand. In this research work, the traffic flow pattern is analysed based on UETAM. However, the FCS planning scheme may affect the traffic flow distribution. And therefor, further considerations like traffic congestion, traffic flow re-distribution and emergency control can be explored in the future work. On the other hand, the planning scheme for controlled EV charging facilities can also be an area that will be explored in the future work.

This research work also develops a planning scheme integrated both the future charging facilities and renewable generation in power system planning. The installation of DG is beneficial to avoid both distribution line expansion and fossil fuel plant construction. The sites and sizes of DG is properly planned to achieve the benefits from DG integration, such as loss reduction, peak load shaving, voltage drop control and investment deferral. This simultaneous optimal planning (placing and sizing) of EV charging system and DG deliver a holistic solution for system planning. Due to the inaccessible of reliable EV driving and charging data, the modelling may not accurate or complex. However, it is reasonable at this stage to deal with the facility planning issue. The work in this area will be enhanced with the availability of data that indicates charging characteristics and user habits, information that will not be available prior to significant EV penetration level. On the other hand, employing controlled charging of EVs in a charging station integrated to photovoltaic is a possible method to decrease greenhouse gas emission.

Lastly, a planning scheme of PV & storage system design with optimized size under different consideration is also achieved, and an algorithm for EMS was constructed. For the system performance, an evaluation that is close to actual condition is provided in this project. The economic performance of system and battery size optimization is evaluated based on current actual data in practical market and the future scenarios. For future study, the system could be extended to suit the future prospective condition, i.e. the widely development of electrical vehicles charging post in commercial building car park. Moreover, we could extend battery life by 'balancing' them, drawing on batteries as individual units, which could enable to make full use of the battery. A larger number of scenarios should improve the solutions generated by better incorporating the stochastic variables, but this imposes greater computational burden. Therefore, heuristic scenario reduction techniques are employed to obtain a scenario setoff size J, which can be solved within a given time with reasonable accuracy.

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APPENDIX A 54-Node Distribution Test System and 25-Node Transportation Test System

A.1 54-Node Distribution System

System Parameter	Value
Nominal Voltage	15kV
Voltage Thresholds	5%, 8%
No. of Nodes	50
No. of branches – total	64
No. of potential branches	48





Fig. A.1 54-Node Distribution Test System Topology [202]

A.2 25-Node Transportation System

Line	Length / km	Weight	Line	Length / km	Weight
1 - 2	40	54	11 - 13	30	5
1 - 5	50	54	11 - 16	70	5
2 - 3	30	80	11 - 12	20	5
2 - 4	40	80	12 - 15	40	54
3 - 4	40	27	12 - 16	40	54
3 - 9	40	27	13 - 14	70	5
4 - 9	70	27	13 - 19	40	5
4 - 8	50	27	14 - 19	70	54
4 - 7	50	27	14 - 21	20	54
4 - 5	30	27	14 - 22	40	54
5 - 6	50	27	15 - 16	40	27
5 - 7	50	27	16 - 17	40	27
6 - 7	30	7	17 - 18	30	27
7 - 8	30	5	17 - 19	30	27
7 - 11	80	5	18 - 20	30	107
7 - 12	90	5	19 - 20	30	80
8 - 9	60	54	20 - 21	20	27
8 - 10	60	54	21 - 14	20	27
8 - 11	70	54	21 - 20	20	27
8 - 13	70	54	22 - 23	30	54
9 - 10	60	27	23 - 24	30	5
10 - 13	60	54	24 - 25	80	134
10 - 14	30	54	25 - 24	80	5

 TABLE A-2
 25-Node Transportation Test System Topology



Fig. A.2 25-Node Transportation Test System Topology [147]