Modelling of Large-Scale Electric Vehicles Charging Demand: A New Zealand Case Study

Jun Su *, T.T. Lie , Ramon Zamora

Department of Electrical and Electronic Engineering, Auckland University of Technology, 34 St Paul Street, Auckland, 1010, New Zealand

Abstract

Due to increasing electric vehicles (EVs) uptakes, power system distribution network will have to accommodate the increased load level for charging EVs. Thus, the importance of a robust power system especially in the distribution network level is indisputable. During the planning or reinforcement stage of distribution networks, it is paramount to have some estimations and analyses done on system-wide EV charging loads that will be placed in the network. Thus, this paper systematically investigates the EV fleet composition, market shares, and charging patterns within New Zealand (NZ) area. A multivariate probabilistic modelling of dependent random variables and cumulative distribution functions is adopted for the accurate estimation of aggregated EV charging demands. Several vehicle travel survey data sets are utilised to quantitatively determine charging behaviours and driving patterns of EVs. The developed methodology based on Monte-Carlo simulation (MCS) is utilised to generate results close to the real use-cases daily power demand, which can be further utilised in the analysis of EV charging strategies. In addition, non-smart

* Corresponding author. Tel.: +64 22 1611 032;

E-mail address: jun.su@aut.ac.nz

and smart EV charging strategies are introduced to mitigate impacts of the large-scale EV deployment and to guarantee the charging completion for each EV.

Keywords: Charging, EV electrical load model, Probabilistic modelling, Smart charging strategies

* Corresponding author. Tel.: +64 22 1611 032;

E-mail address: jun.su@aut.ac.nz

1. Introduction

During the last decade, the reduction of fossil fuel dependency and the reinforcement of environmental policies had motivated the automotive industry to shift development directions from conventional internal combustion engine vehicles (ICEVs) to electric vehicles (EVs). Both opportunities and challenges of EV deployments need to be identified in the electricity industry to achieve better integration at the planning and operational levels [1]. Along with expected environmental benefits, the increasing penetration of EVs may potentially reshape electricity load profiles due to the grid-to-vehicle and vehicle-to-grid power flow [2].

EV deployment impacts on transportation, manufacturing, economy or long-term power system plan have been identified, studied and quantified mainly by means of mathematical, deterministic and probabilistic models. Such models are necessary primarily for two reasons. Firstly, real world data about EV use is not publicly available due to the privacy concern and the low EV uptake to date. Secondly, although data is available, there will still be a concern on how to make use of the data to access and mitigate impacts for the conditions with different EV charging and driving patterns [3]. Moreover, the EV charging demand is considered as an essential input for EV charging strategies to carry out scheduling subject to a set of constraints. In order to demonstrate the convincing effectiveness of EV charging strategies, it is necessary to consider the randomness and heterogeneity of EV charging demands.

Reviews of the studies into the modelling of EV charging demand have been carried out to identify the weakness and strength in each approach [3]. The studies conducted in Refs. [4, 5] proposed mathematical analyses of EV charging demands, in which the fluid dynamic traffic model and the queueing theory were utilised to evaluate the charging demands regarding spatial and temporal dynamics. The Markov chain models were built in Refs. [6, 7], uncertainties related to when and where EVs will be recharged were pre-defined by a global transition matrix in which charging events for the next time interval were only influenced by pre-determined transition probabilities. In deterministic studies, distribution network constraints were utilised to estimate the threshold level of EV penetrations that would exceed thermal ratings [8-10]. In probabilistic studies, stochastic procedures are used to complete the quantitative analysis [11]. The national transport survey was adopted in support of the extraction of probability density functions. The method of Monte-Carlo Simulation (MCS) was presented in Refs. [7, 12], where loading profiles with the integration of EVs were acquired by probabilistic density functions (PDFs). The study [13] also employed MCS to evaluate EV deployment impacts on a distribution network with increasing penetration levels.

The diverse stochastic techniques become a popular choice to generate EV charging data, which is considered as essential input parameters of controlled or optimised charging strategies to evaluate EV deployment impacts. Different charging algorithms, methods and strategies in the field of smart EV charging systems were reviewed in [14]. A number of metaheuristic approaches can be found in centralised and decentralised charging strategies that manage EV charging behaviours to achieve optimisation targets, such as the minimum cost, the minimum power variance and the minimum emission [13, 15, 16]. The scheduling of EV charging loads in each domain is carried out by measuring local parameters or associated criteria, such as tariff signals or local electrical signals [17-21].

A rigorous estimation of EV deployment impacts at the system level is considered important for distribution network operators (DNOs) in the planning phase of network reinforcements. Most of the existing research works evaluate EV deployment impacts mainly based on reasonable assumptions about the randomness characteristic while ignoring the heterogeneity characteristic. For instance, in [7], the authors merely made use of a BMW i3 model to represent all EVs within the distribution network. The fixed EV plug-in time and plug-out time were assigned in [9] to simulate the worst-case scenario in which the EV charging demand overlap the peak residential loads. The study [22] introduced an example of the stochastic charging scenario with the application of the conditional Gaussian distribution to simulate arrival times, charging times and departure times for an EV fleet. A probabilistic model of EV driving patterns was developed in [6] based on different PDFs extracted from transportation survey data, but only one charging mode was considered in the model.

The research gap among these studies is the lack of consideration for heterogeneity in the modelling of EV charging demands so that the effectiveness level of charging strategies is not convincing. Such heterogeneity in EV charging loads is composed of factors that will change the profiles of EV charging loads, such as different daily driving mileages, recharging times and different compositions of EV fleets. For example, equivalent numbers of commercial EVs and private EVs may result in entirely different charging demands, which has been investigated in [23]. More importantly, despite the importance of EV charging behaviours in fore-mentioned works summarised, current smart charging strategies primarily rely on the simplistic representation of EV charging and travel behaviours. The promotion of EV usages will potentially alter the transport and electricity network. Hence, it is necessary to develop an empirically estimated model amenable for these integrated cross-sector analyses based on existing statistics data available. By this modelling technique, the proposed EV charging strategies can be carried out to validate the performance and effectiveness closer to a real case.

From the practical operation view, the EV scheduling problem is formulated as an optimization model in this paper in order to identify the grid benefits solution that satisfies the charging requests. Therefore, the main contributions of the paper are:

1. A large-scale EV charging model that bridges the gap between the representations of charging behaviour used in integrated transport and power system analyses for the appraisal of smart charging strategies.

2. A multivariate probabilistic model to estimate aggregated EVs charging loads with the consideration of randomness and heterogeneity based on transportation statistic data.
3. A case study to test effectiveness of non-smart and smart charging strategies regarding peak-shaving and valley-filling impacts on the aggregated EVs charging loads.

The rest of the paper is organised as follows. The EV charging and driving patterns considering all relevant factors are explained in Sections 2 and 3. Section 4 provides the modelling approach based on MCS. Then, the charging strategies and a case study are described in Section 5. The results and discussion are presented in Section 6, and the paper is concluded in Section 7.

2. EV Fleets Composition in NZ

The 2018 annual vehicles statistic from NZ Ministry of Transport [24] indicated that over 7000 Electric Vehicles (EVs) are running on the road, 49% of which are concentrated in Auckland as presented in Fig. 1~~Fig. 1~~. As shown in Table 1~~Table 1~~, although the EV penetration in NZ has experienced a rapid growth in recent years, it merely occupied nearly 0.1% in 2017 [24]. The EV penetration represents the percentage of the total EVs number over the total vehicles number.

Table 1 EV penetrations in New Zealand from 2014 to 2018

Year	EVs Number	Annual EVs Fleet Growth	EV Penetration
2014	232		0.01%
2015	592	255.17%	0.02%

2016	1114	188.18%	0.03%
2017	2752	247.04%	0.07%
2018	7000	240.30%	

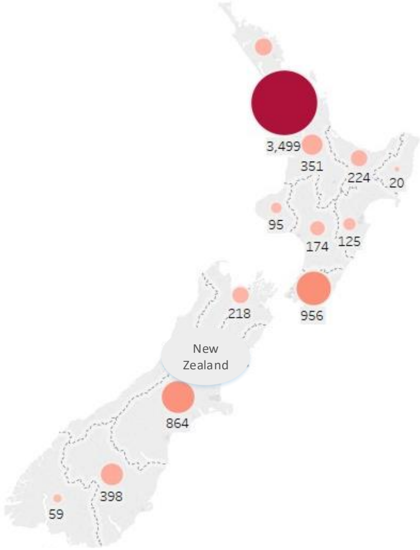


Fig. 1. EVs Distribution Map in New Zealand in 2018

2.1 Projected Ownership of Electric Vehicles

The EV population is a critical determinant of EV charging demands. The New Zealand Center of Advanced Engineering (CAENZ) proposed four scenarios about future EV uptakes in [25] based on NZ government and consulting company works as shown in Table 2~~Table 2~~.

Table 2 Predicted EV populations in NZ

Years	EV uptake scenarios (unit: millions)	
	Lower Case	Upper case
2040	0.9	2
2030	0.3	1.2
Current	0.007	

2.2 Projected EV Fleets Composition

EV populations can be categorized into five main fleets according to EV ownership statistics in NZ, which are private EVs, utility EVs, commercial EVs, electric goods trucks, and electric buses [24]. The fleet categories include a variety of EV manufacturers, in which each brand has its own endurance mileage, battery capacity and charging power.

Table 3

Table 3~~Table 3~~ introduces five mains EV models to represent each EV fleet in the modelling of charging demands. Their technical parameters will be used in MCS. Fig. 2~~Fig. 2~~ depicts the composition ratio of ICEV fleets in NZ [24]. The present and projected amount of various EV fleets in Table 4~~Table 4~~ are derived from predicted EV populations in Table 2~~Table 2~~ with the assumption that the composition ratio of the five EV fleets is equivalent to that of the ICEV fleets in Fig. 2~~Fig. 2~~.

Table 3 Charging parameters of five types of EV models

EV types	Manufacturers Model	Battery Capacity (kWh)	Charging Power(kW)		Full endurance mileage (km)
			Slow Charging	Quick Charging	
Private Vehicle	Nissan-Leaf	24/40	6.6	11	150/250
Utility Vehicle	Nissan-Leaf	40	6.6	11	250
Commercial Vehicles	Nissan-Leaf	40	--	11	250
Goods Truck	EMS 18 series	240	--	80	250
Bus	AUT-BUS	202	--	50	200

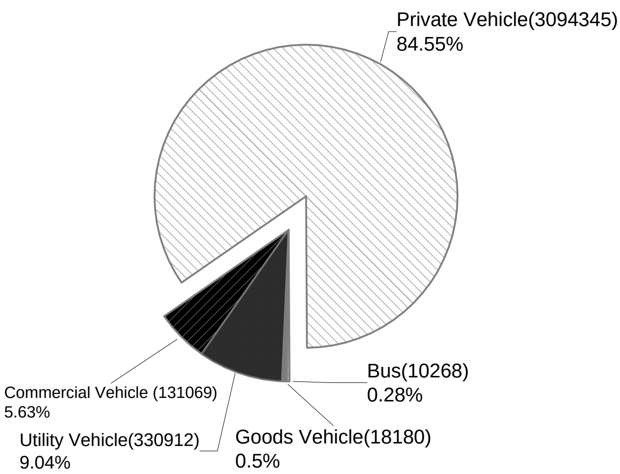


Fig. 2 2018 composition ratio of ICEV fleet in NZ

Table 4 The present and projected EV fleets in NZ

EV uptake scenarios	Private Electric Vehicle	Electric Utility Vehicles	Electric Commercial Vehicle	Electric Goods Truck	Electric Bus
2018 Uptake	5919	633	394	35	20
2030 Lower Case Uptake	253660	27127	16881	1490	842
2030 Upper Case Uptake	1014641	108507	67524	5961	3367
2040 Lower Case Uptake	760981	81380	50643	4471	2525
2040 Upper Case Uptake	1691068	180844	112540	9935	5611

3. Analysis of EV Charging Behaviour

Some existing studies [6, 7, 22, 26] in the appraisal of charging strategies relied on simplistic representation of EV fleets conforming to a certain probability model, which merely considered randomness of charging behaviours while ignoring heterogeneity. A multivariate probabilistic model is introduced to characterise both randomness and heterogeneity in the modelling of EV charging demand based on the summary statistics in NZ. Such model can be used to represent of consistent charging behaviours used in integrated transport and power system analyses. It is assumed that advent of EVs will not affect daily travel patterns and lifestyles in general so that EVs have similar driving patterns with ICEVs. The following uncertainty factors are considered when modelling the 24-hour EV charging demand: (i) EV charging duration, (ii) EV charging power, (iii) EV daily travel distance/EV initial battery SoC, (iv) EV recharge probability, (v) EV plug-in time. These uncertainties were treated separately for each EV, which are random variables generated by predefined PDFs in Table 5~~Table 5~~.

The PDFs of EV daily driving distances are either of normal or logarithmic distribution type ~~in previous studies~~ with a positive value of the travel distance [27-29]. It can be expressed by Eqs. (1~~(1~~) and (2~~(2~~), respectively.

$$f_{D1}(x_{i,j}) = \frac{1}{\sigma_{D1,j}\sqrt{2\pi}} exp\left[-\frac{(x_{i,j}-\mu_{D1,j})^2}{2\sigma_{D1,j}^2}\right], x > 0 \qquad (1)$$

$$f_{D2}(x_{i,j}) = \frac{1}{x\sigma_{D2,j}\sqrt{2\pi}} exp\left[-\frac{(lnx_{i,j}-\mu_{D2,j})^2}{2\sigma_{D2,j}^2}\right], x > 0 \qquad (2)$$

where $i = \{1,2,3 \ldots N_j\}$ represents ith EV in the specific EV fleet, $j = \{1,2,3,4,5\}$ is the total vehicle amount in the specific EV fleet, specifically 1: private EVs, 2: utility EVs, 3: commercial EVs(taxies), 4: electric goods trucks, 5: electric buses. $x_{i,j}$ is the daily travel distance of an EV, $\mu_{D1,j}, \mu_{D2,j}$ are mean values, and $\sigma_{D1,j}, \sigma_{D2,j}$ are standard deviation values. For different EV fleets, the corresponding mean values and standard deviations are defined in Table 5~~Table 5~~.

The endurance mileages of different EV models are related to their corresponding battery capacities. Given the full endurance mileage D_j, the initial state of charge $SOC_{i,j}$ can be estimated by Eq. (3~~(3~~).

$$SOC_{i,j} = 1 - \frac{d_{i,j}}{D_j * \eta_1}, \quad 0.05 \leq \frac{d_{i,j}}{D_j * \eta_1} \leq 0.95 \qquad (3)$$

where $d_{i,j}$ represents the daily travel distance of i^{th} EV, which is a random variable derived from Eqs. (1~~(1~~) and (2~~(2~~). All vehicles need to be fully charged before the next journey starts.

Various studies about the efficiency of EV powertrain have been carried out to include the loss of battery power in driving cycles and the battery life cycle [30, 31]. This study considered $\eta_1 = 0.95$ to represent the loss of battery power during EV running.

The plug-in time $tp_{i,j}$ is given in Eq.(4~~(4~~).

$$f_t(tp_{i,j}) = \frac{1}{\sigma_{t,j}\sqrt{2\pi}} exp\left[-\frac{(tp_{i,j} - \mu_{t,j})^2}{2\sigma_{t,j}^2}\right] \qquad (4)$$

where $tp_{i,j}$ is the plug-in time of an EV, $\mu_{t,j}$ is the mean value, and $\sigma_{t,j}$ is the standard deviation. For different EV fleets, the corresponding values of $\mu_{t,j}, \sigma_{t,j}$ are defined in Table 5~~Table 5~~.

For each EV, $tc_{i,j}$ is the charging duration of i^{th} EV in j^{th} fleet type, $Cap_{i,j}$ is the full battery capacity, charging efficiency η_2 is 0.95 in all cases, N_j is the total number of the specific EV fleet. $td_{i,j}$ is the charging duration to reach $SOC_{i,j} =$

0.95 with rated charging power $P_{C_{i,j}}$ defined in Table 3~~Table 3~~. $P_{EV_{i,j}}(t)$ is the charging power of each EV at time t, $P_{EV}(t)$ the total EV charging power at time t.

$$tc_{i,j} = \sum_{i=1}^{N_j}(0.95 - SOC_{i,j}) \times \frac{Cap_{i,j}}{P_{C_{i,j}} \times \eta_2} \quad (5)$$

$$td_{i,j} = tp_{i,j} + tc_{i,j} \quad (6)$$

$$\begin{cases} P_{EV_{i,j}}(t) = P_{C_{i,j}}, & tp_{i,j} \le t \le td_{i,j} \\ P_{EV_{i,j}}(t) = 0, & other\ time \end{cases} \quad (7)$$

$$P_{EV}(t) = \sum_{j=1}^{5}\sum_{t=i}^{N_j} P_{EV_{i,j}}(t) \quad (8)$$

Over 80% of light vehicles were parked overnight at private residences or private off-street locations [25]. The assumptions in this model are to consider that 80% of the private EVs plug in the charging infrastructure during the off-work period 18:00 p.m.-next 07:00 a.m. and the remaining 20% will be recharged during working hours 9:00 a.m.-17:00 p.m. The values of μ_{D2} and σ_{D2} for private EVs are considered to be 3.2 and 0.92 respectively based on the average daily travel distance of 23.2 km specified in [25]. Due to the absence of travel data on utility EVs, it is assumed that it has the same driving pattern with private EVs. Typically, there are three working shifts for commercial EVs (Taxies) per day, 0:00-9:00, 9:00-16:00, 16:00-24:00. In Ref. [32], authors pointed out driving distances of taxi drivers in every driving shift are ranging from 33 km to 350 km (an average of 195.49 km, μ_{D1}, std. dev. of 49.99, σ_{D1}), thus charging twice a day is necessary to support the driving requirement. It is reasonable to assume that commercial EVs are quite likely to be charged with the fast charging mode because the shorter charging time implies longer service hours to make profit. A survey of 95 truck drivers carried out in Ref. [32] also revealed that daily driving distances are ranging from 38 km to 500 km (an average of 201.80 km, μ_{D1}, std. dev. of 94.42, σ_{D1}). Two charging times and the high charging mode are essential to electric goods trucks as well. The electric buses are usually recharged with the high charging mode during off-service periods. As electric buses have relatively fixed daily routes so that their daily travel distances are relatively stable. The probability distribution parameters are $\mu_{D1} = 155, \sigma_{D1} = 10$ according to electric bus operation data from Auckland University of Technology [33].

According to the summary of travel survey discussed above, Fig. 3~~Fig. 3~~ presents the probability distributions of five EV fleets' daily travel distances. The corresponding PDFs parameters are summarised in Table 5~~Table 5~~.

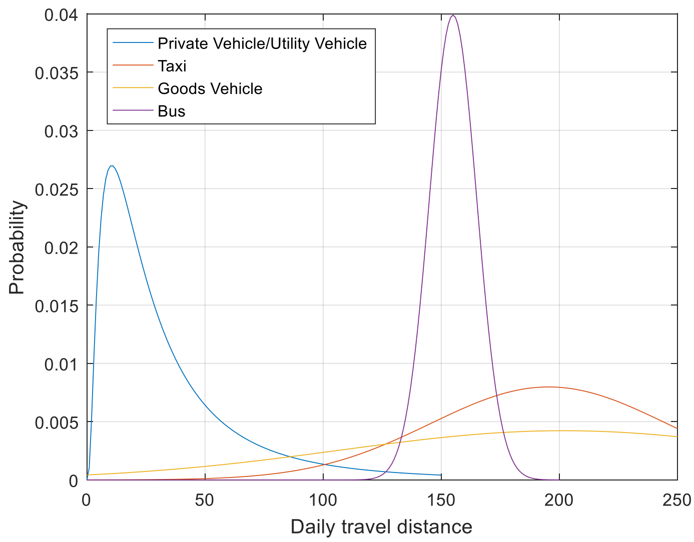


Fig. 3 Probability distributions of daily travel distances by vehicle types

Table 5 Characteristic EV charging parameters for probabilistic modelling

	Daily Charging Times	Charging Period (Tp, Td)	Charging Mode M_C	Probability	Initial $SOC_{i,j}$ Distribution	Plug in time $tp_{i,j}$
Electric Private Vehicle	1	9:00~17:00	slow	10%	Equation (5.3) based on log N (3.2,0.92)	N(9,0.9)
		18:00~07:00	slow	80%		N(18.5,1)
		09:00~17:00	fast	10%		Even Distribution
Electric Utility Vehicles	1	9:00~17:00	fast	30%	Equation (5.3) based on log N (3.2,0.92)	N(12,0.9)
		18:00~07:00	slow	70%		N(18.5,1)
Electric Commercial Vehicles	2	00:00~09:00	fast	90%	Equation (5.3) based on N(195.49,49.99)	N(4,2.5)
		09:00~16:00	fast	60%		N(12,2.5)
		16:00~24:00	fast	50%		N(18,1.5)
Electric Goods Trucks	2	00:00~09:00	fast	80%	Equation (5.3) based on N(201.8,94.42)	N(3,1.5)
		09:00~24:00	fast	120%		N(14.5,2.8)
Electric Bus	1	22:00~07:00	fast	100%	Equation (5.3) based on N(155,10)	N(22,0.5)

N ($\mu_{D1,j}$, $\sigma_{D1,j}$): normal probability distribution function. Log N ($\mu_{D1,j}$, $\sigma_{D1,j}$): logarithmic probability distribution function. $(Tp_{i,j}, Td_{i,j})$: charging period constraints.

4. Modelling Method of EVs Charging Load

4.1 Monte Carlo Simulation

The multivariate probabilistic model in MCS aims to estimate EV charging demands according to the transportation statistics data in New Zealand. The following are assumptions made for the simulation conducted in this paper:

a. Charging facilities are enough so that the EV owners start charging immediately once parked.

b. The generation capacity is enough to supply EV loads.

c. The charging power is rounded to the nearest integers toward infinity in the hourly charging power calculation

4.2 Calculation Process of EV Charging Load based on MCS

In the MCS, $tp_{i,j}$, M_C and $SOC_{i,j}$ are independent stochastic variables for each EV, which are generated based on the modelling parameters in Table 5~~Table 5~~. The MCS schematic process is presented in Fig. 4~~Fig. 4~~, specifying the following steps:

1. Initiate EV modelling parameters listed in Table 3~~Table 3~~ and Table 4~~Table 4~~.
2. Based on the probability density functions of stochastic variables, EV charging demand data is generated by Eqs. (1~~(1~~)-(4~~(4~~).
3. Get the charging load of each EV based on Eqs. (5~~(5~~)-(6~~(6~~).

4. Accumulate the charging load of each EV. Loop counts until total EV calculation complete by Eq. (7~~(7~~)-(8~~(8~~).

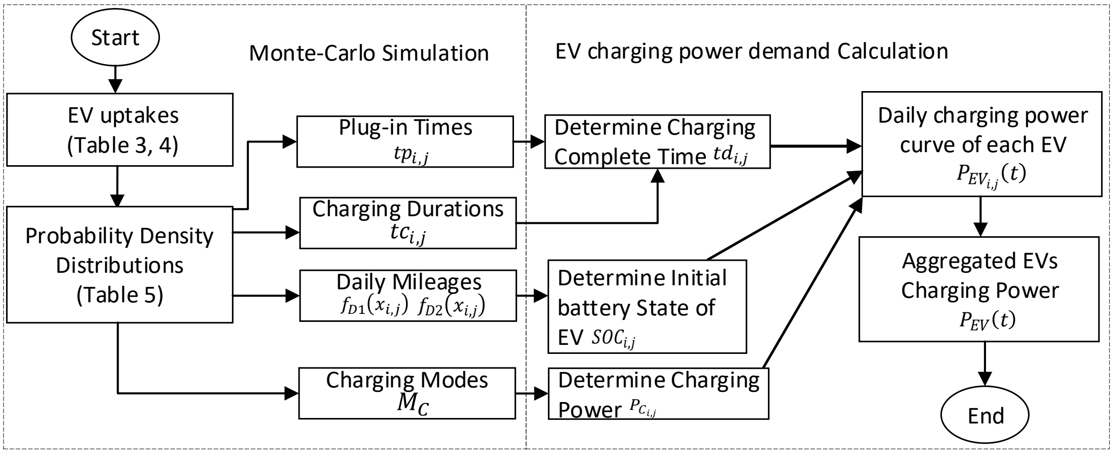


Fig. 4 The schematic process of EV charging demands simulation

5. EV Charging Strategies

According to empirical estimations, private EVs, utility EVs and electric buses have more charging flexibility during the night. In contrast, commercial EVs and electric goods trucks are essential to be fully charged within the shortest time for the next driving work so that they are not participated in charging strategies.

The flowchart of the proposed EV charging strategies is displayed in Fig. 5~~Fig. 5~~. The input parameters for each charging strategies are obtained from the MCS. The targeted EV fleets selected by the proposed charging strategies are private EVs, utility EVs and electric buses when they plug in networks after Tp=18:00 p.m. and plug out before Td=next 7:00 a.m. (next day usage constraint). Optimization algorithms aims to achieve peak-shaving and valley-filling effect on the typical daily power curve, and at the same time, to guarantee selected EV fleets to be fully charged before expected usage time 7:00 a.m.

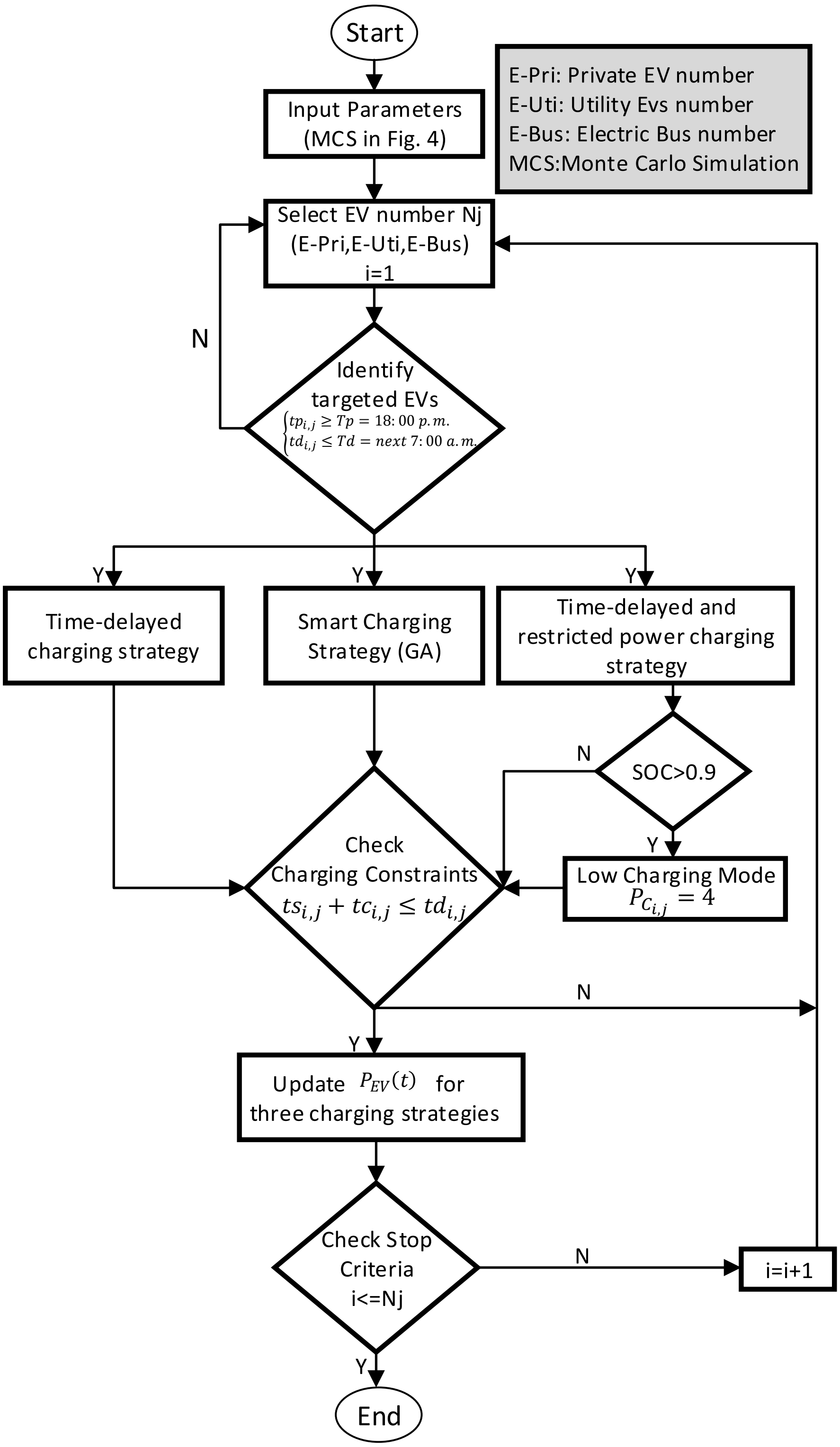


Fig. 5 Flowchart of EV charging Strategies

5.1 Non-smart EV Charging Strategies

5.1.1 Time-Delayed EV Charging Strategy

EV charging data is obtained from MCS described in Fig. 4~~Fig. 4~~. The selection process of specific EV fleets for the charging strategy is presented in Eq. (9~~(9~~): Only private EVs, utility EVs and electric buses are considered in the charging strategy. The scheduling duration is between 18:00 p.m. and next 7:00 a.m.

$$\begin{cases} tp_{i,j} \geq 18:00\ \text{p.m.} & j = \{1,2,5\} \\ td_{i,j} \leq \text{next } 7:00\ \text{a.m.} & j = \{1,2,5\} \end{cases} \quad (9)$$

Eq. (10~~(10~~) delays start charging time $ts_{i,j}$ by 3 hours since EV plug-in time $tp_{i,j}$ and verifies charging period constraints to make sure that each EV completes the charging before $td_{i,j}$ (the next day expected usage time 7:00 a.m.)

$$\begin{cases} ts_{i,j} = tp_{i,j} + 3 & j = \{1,2,5\} \\ ts_{i,j} + tc_{i,j} \leq td_{i,j} & j = \{1,2,5\} \end{cases} \quad (10)$$

5.1.2 Time-Delayed and Restricted Power EV Charging Strategy

This charging strategy combines the time delayed process and the restricted charging power process. The time-delayed process is the same as described above. The additional restricted power process is to assign a new charging power $P_{C_{i,j}} = 4$ kW instead of 6.6 kW, to private EV and utility EVs if the initial battery SoC is over 0.9, as described in Eq. (11~~(11~~)

$$\begin{cases} P_{C_{i,j}} = 4, for\ 0.9 < SOC_{i,j} \leq 1 \\ P_{C_{i,j}} = 6.6, for\ 0.05 < SOC_{i,j} \leq 0.9 \end{cases} \quad (11)$$

5.2 Smart Charging Strategy based on Genetic Algorithm

The same EV fleets and scheduling duration as previously described are considered in the smart charging strategy. The objective function in Eq. (12~~(12~~) is to minimize the peak-valley difference on power curves by applying Genetic Algorithm (GA). The decision variable in Eq. (13~~(13~~) is the start charging time $ts_{i,j}$ of each EV.

- Objective Function

$$Min \sum_{t=1}^{T} P_{T.var}(t) = P_{T.max}(t) - P_{T.min}(t) \quad (12)$$

- Decision Variable

$$tp_{i,j} < ts_{i,j} \leq td_{i,j} - tc_{i,j} \quad (13)$$

- Charging Conditions

In the smart charging strategy, the charging power of each EV is set up based on Eq. (11~~(11~~) as well, except for electric buses with the high charging mode. The total charging power are calculated according to Eq. (14~~(14~~) and Eq.(15~~(15~~).

$$\begin{cases} P_{EV_{i,j}}(t) = P_{C_{i,j}},\ ts_{i,j} \leq t \leq ts_{i,j} + tc_{i,j} \\ P_{EV_{i,j}}(t) = 0, other\ time \end{cases} \quad (14)$$

$$P_T(t) = P_{base}(t) + P_{EV}(t) \quad (15)$$

where $P_{base}(t)$ is the original demand-side base load at time t, $ts_{i,j}$ is the start charging time; in the smart charging strategy, the EVs do not have to be recharged once parked. The start charging times is subject to the optimization process. $P_{T,\max/min}(t)$ is the total electrical load at time t. The subscripts mean maximum and minimum values.

5.3 Genetic Algorithm Implementation

An appropriate scheduling of the charging times may lead to energy savings, but at the same time, it also increases the complexity as it needs to satisfy constraints from a set of EV users and the electrical network. The choice of scheduling optimisation algorithms depends on several aspects, such as the computation time, the required quality of solutions, and the selection of the problem's constraints or objective functions.

The use of GA has been discussed in Refs. [15, 34-36] as a well-established heuristic approach to compute EV scheduling. In particular, the natural evolution character of GA is able to make the process more likely to converge to a global optimum. Therefore, it has been proven to be robust optimisation techniques dealing with non-linear and non-convex problems in the EV scheduling [34]. Also, GA has the ability to work with search spaces by using multiple points of the population and iterative characteristics and to exploit any kind of heuristic knowledge from the problem domain, and by doing so, it is competitive with the most efficient methods in the scheduling [36]. Given that decision variables used in this study are a type of floating numbers, according to the satisfactory performance of GA for discrete spaces [15], GA was selected to solve EV scheduling problems in this study.

In this article, three adjustable parameters *P*, *Cr*, *Mr* need to be defined to solve the scheduling problem. *P* is the population size in each generation (alternatively iteration), which directly affects the computation time and convergence rate. In genetic operators, *Cr* and *Mr* are crossover rate and mutation rate, respectively, to enable GA to enhance search capability. The adjustment of *P*, *Cr* and *Mr* tries to remove the undesirable response and to obtain more optimal solutions at the given computation time step. A sensitivity analysis based on the empirical method is conducted to determine values of *P*, *Cr* and *Mr*, aiming to achieve lowest mean fitness of the obtained results in each generation, in other words, to achieve the lowest power variation on the load curve, as displayed in Fig. 9~~Fig. 9~~b. With a population size of 10, cases 1-3 in Fig. 6~~Fig. 6~~ demonstrate that *Cr*=0.8 and *Mr*=0.1 obtain the highest computing efficiency. The purpose of cases 4-6 in Fig. 6~~Fig. 6~~ is to find an appropriate value of population size (*P*=300) to obtain the best solution set at the given computation time step, which is considered as 3 minutes for 2018 EV uptake.

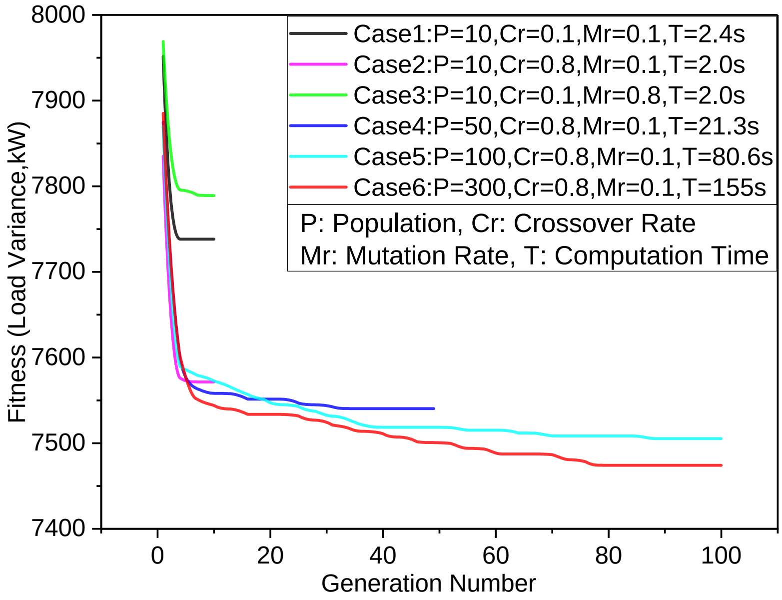


Fig. 6 The average fitness of the population in the parameter tuning

The GA implementation begins with the encoding, in which EV charging data specified in Table 5~~Table 5~~ is used as constraints ($tp_{i,j}, td_{i,j}$) to determine the feasible solution space of the population. The decision variable $ts_{i,j}$ for a set of EVs are encoded into a chromosome of parent generation. The population size (P=300) in each generation is composed of 300 chromosomes. The chromosome of offspring generation inherits part of genes from the parent generation while also receives some modified part of gene from crossover and mutation operator, which can be described as the global searching capability for the decision variable in Eq.(13~~(13~~). A proper fitness function described in Eq. (12~~(12~~) is designed to search a potential set of $ts_{i,j}$ to give a lowest grid load variance, at the same time, to guarantee selected EV fleets to be fully charged before expected usage time 7:00 a.m. The loop iteration will repeat again to produce new generations until iteration converges to stopping criteria.

5.4 *Case Study*

A case study is utilized to evaluate the effectiveness of the proposed charging strategies. The Auckland real-time base load and demand-side wholesale electricity price from [37] are used in the simulation. The NZ 2030 lower case EV uptake is considered in the Auckland city case study. There will be 0.3 million EVs running on the road, 49.9% of which are in Auckland District. The composition ratio of five EV fleets is based on the current statistical data introduced in Fig. 2~~Fig. 2~~. The total charging cost of EV could be estimated based on Eq. (16~~(16~~).

$$Tcost = WEprice(t) \times P_{EV}(t) \tag{16}$$

where $WEprice(t)$ is demand side wholesale electricity price.

5.5 *Applicability and Limitations*

The modelling of EV charging demand could be either on-line or off-line. In the off-line system, the EV travel and charging patterns were extracted from summary statistics, as the real world data about EV use is not publicly available. The variability of EV travel and charging patterns could be redefined in Table 5 to access short-term EV charging demand if on-line charging events data can be obtained. The modelling process may appear suitable for long-term planning, such as planning of power generation capacity, planning of network reinforcement.

The proposed strategies can be potentially applied for on-line smart charging systems. Fig. 7~~Fig. 7~~ displays a schematic structure of the on-line smart EV charging system. Start charging times $ts_{i,j}$ of EVs are considered as decision variables in the optimisation process. The data communication between EV chargers and local servers could be realized by either wire or wireless technology, such as internet of things and the power line communication. Overall, the operation of the system is based on the event-driven architecture. The main event in this system is the occurrence of EVs plug-in and plug-out. In this methodology, EV users, EV chargers, local servers and main server should perform a set of tasks, as shown in the following process:

- Every EV charger transmits battery parameters and requests a start charging time for the specific parking duration and the expected battery SoC set by the user.
- The local server acts as a data aggregator to collect all EV charging requests within its domain at each computation time step (3 minutes).
- The main server executes the optimal charging algorithm taking into account all EV chargers' data and predicted base loads at the current time step. The scheduled start charging times $ts_{i,j}$ are sent back to all chargers through local servers.
- The requested EV chargers update the charging schedule and execute it.
- Any charging process is interrupted before the estimated plug-out time. EV chargers will send a disconnection request to the local server.
- The main server will receive interrupted charging signals and update new EV charging loads for scheduling in the next time slot.

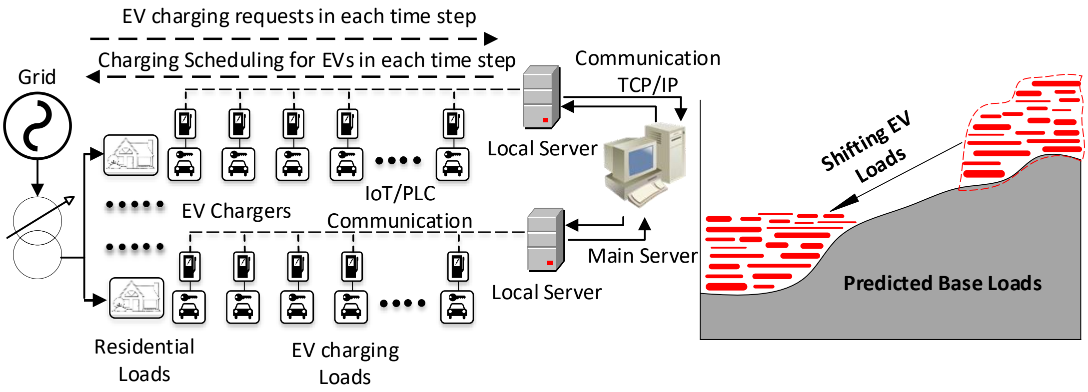


Fig. 7 Schematic structure of a on-line smart EV charging system

6. Results and Discussion

6.1 Free EV Charging Power Demand

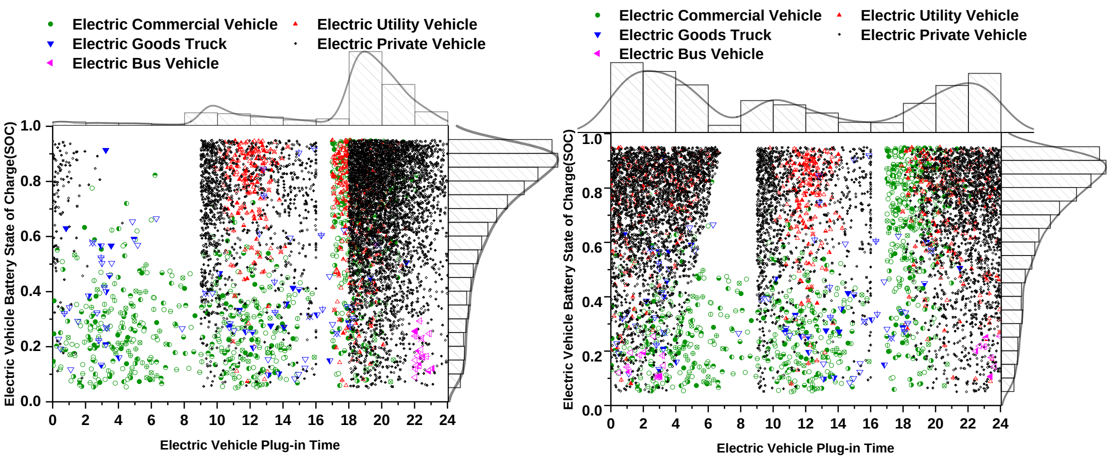
The 2018 EV uptake defined in Table 4~~Table 4~~ have been applied in MCS to generate a charging demand that is closer to the real-case in NZ. The temporal distribution of the uncontrolled EV's charging demand is conducted in the probabilistic model as depicted in Fig. 8~~Fig. 8~~a. The simulation results display private EVs and utility EVs are mainly recharged in early hours during on-work and off-work periods. Due to longer daily travel distances, the electric goods trucks, commercial EVs and electric buses have lower initial battery SoC, represented by blue, green and pink dots.

After the EV charging data is obtained, the total daily EV charging power $P_{EV}(t)$ could be calculated based on the flowchart described in Fig. 4~~Fig. 4~~. By far the greatest charging demand in Fig. 9~~Fig. 9~~a is from private EVs, contributing roughly 14MW rapid growth on the black power curve between 18:00 a.m. and 24:00 p.m. The uncontrolled EV charging scenario gives rise to the overall charging demand at early night with a peak power of 19 MW, which is almost the same time as when households turn their heating, cooking and other appliances on.

The charging period of private EVs, utility EVs and electric buses could be further delayed to avoid peak hours as their charging process almost ends up before 2:00 a.m. when it is still too early for the next day's usage.

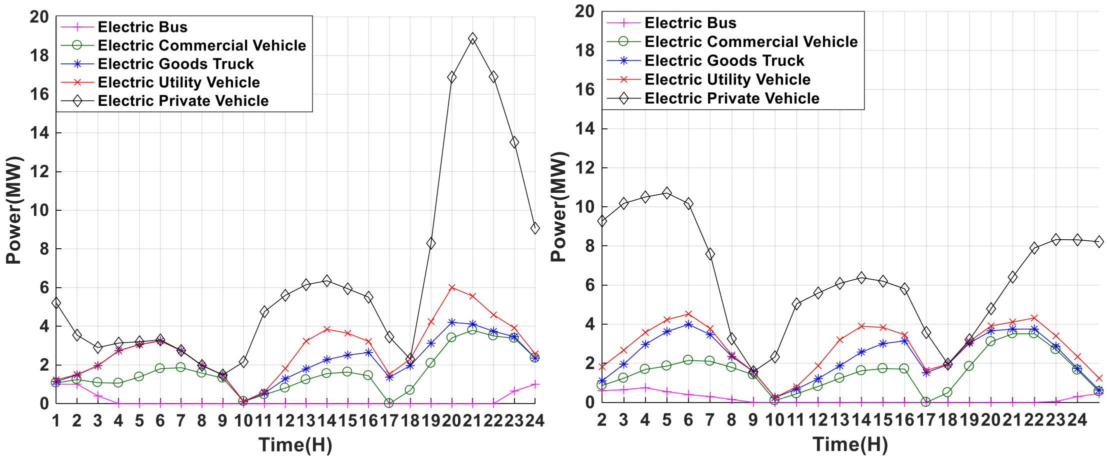
6.2 Coordinated EV Charging Power Demand

The free EV charging load profiles in Fig. 8~~Fig. 8~~a and Fig. 9~~Fig. 9~~a reveals that private EVs and utility EVs are the primary sources contributing to the rapid power raise due to higher penetrations. As introduced in Section 5, three charging strategies are designed to coordinate selected EV fleets when plugged-in during 18:00 p.m.-next 7:00 a.m. without affecting EV use in the next day. Fig. 10~~Fig. 10~~ presents a comparison between coordinated EV charging load curves and original EV charging load curves, where the peak power point was decreased from 19 MW to 12.5 MW and finally levelled out at 10.9 MW in the smart charging strategy. Therefore, it is apparent from Fig. 8~~Fig. 8~~b and Fig. 9~~Fig. 9~~b that the concentrated charging loads in peak hours were delayed to span on off-peak periods to reduce load variance.



(a) (b)

Fig. 8 (a) Scatter plot between plug-in time and initial SoC in 2018 NZ free charging scenario (b) Scatter plot between plug-in time and initial SoC in 2018 NZ smart charging scenario



(a) (b)

Fig. 9 (a) Indicated NZ EV charging profile in 2018 free charging scenario (b) Indicated NZ EV charging profile in 2018 smart charging scenario

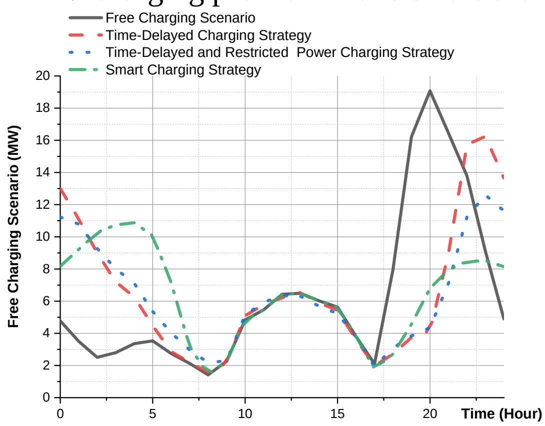


Fig. 10 Indicated NZ EV charging load profile in 2018 with three charging strategies

6.3 Management of EV Charging Demand: Case Study

Currently, there are just 3499 EVs in Auckland and may not lead to a distinct increase in the daily power load profile. Therefore, the 2030 lower case EV uptake is adopted in the case study as detailed in Section 5.4.

Fig. 11~~Fig. 11~~ displays EV deployment impacts on the Auckland electrical load curve (22/05/2018). From the free charging load curve (red dotted), we can see that the peak charging demand coincides with peak hours of the day, leading to a peak power of nearly 1400 MW. Comparing charging load curves in three charging strategies, it is found that there is no noticeable load spike as the peak charging demand is delayed to off-peak periods. Consequently, proposed non-smart and smart charging strategies demonstrate a positive correction on the electricity load profile regarding peak-shaving and valley-filling influences.

The further statistical analysis shown in Fig. 12~~Fig. 12~~ demonstrates effectiveness levels of three charging strategies. The smart charging strategy achieves the best performance to flatten the power curve with a power variance range between 788.55 MW and 1173.83 MW. With the extra EV burden, various power curves have similar mean values nearly 990 MW, which could be explained by the electrical energy consumptions from the same EV uptake. The analysis results are summarised in Table 6~~Table 6~~. In 2030 EV lower case, the growth rate of Auckland peak loads will reach 31% without proper management of the EV charging demands. Whereas, by applying the proposed charging strategies, the growth rate can be restricted to merely 6%~9%. The standard deviation of the electrical loads with integration of EVs decreases from 234 MW to 128 MW. The charging cost savings due to the lower electricity price after midnight gives an economic incentive to EV owner to give up direct control of the charging process.

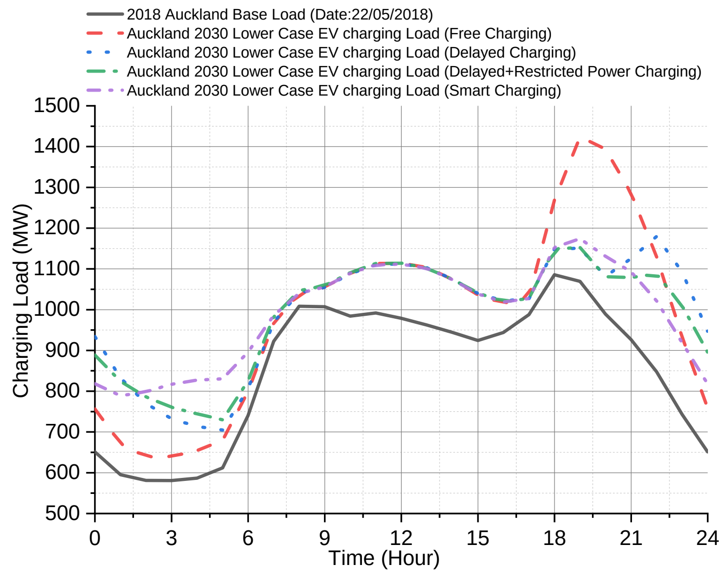


Fig. 11 Indicated EV charging load profile with three charging strategies

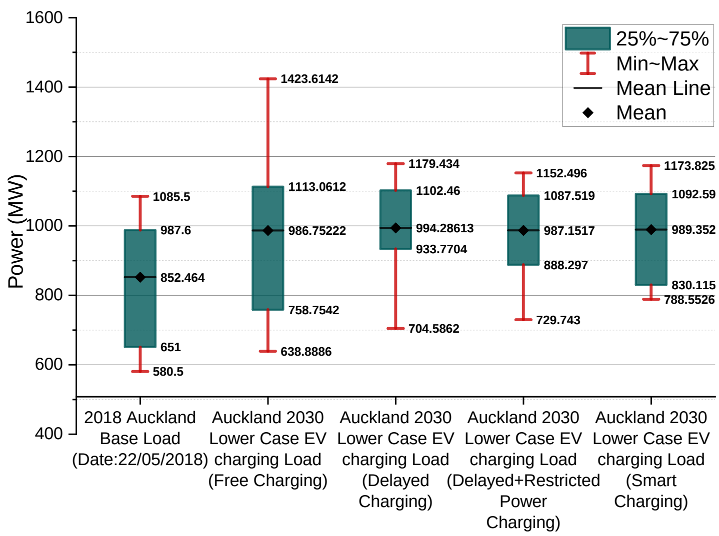


Fig. 12 Box plot of indicated EV charging load profile in 2030 with three charging strategies

Table 6 Charging indexes of large-scale EVs deployment in Auckland power system

	Auckland Electricity Load in 2018	Auckland 2030 Lower Case EV charging Load			
		Free charging	Delayed charging strategy	Delayed and restricted power charging strategy	Smart charging strategy
Peak Load(kW)	1086	1423	1179	1152	1173
Peak Load-Growth Rate		31%	9%	6%	8%
Load Standard Deviation(kW)	175	234	149	136	128
Load Standard Deviation Change Rate		34%	-15%	-22%	-27%
$Tcost$ (Thousands NSD$)		118	109	107	113

6.4 Future EV Deployment Impacts

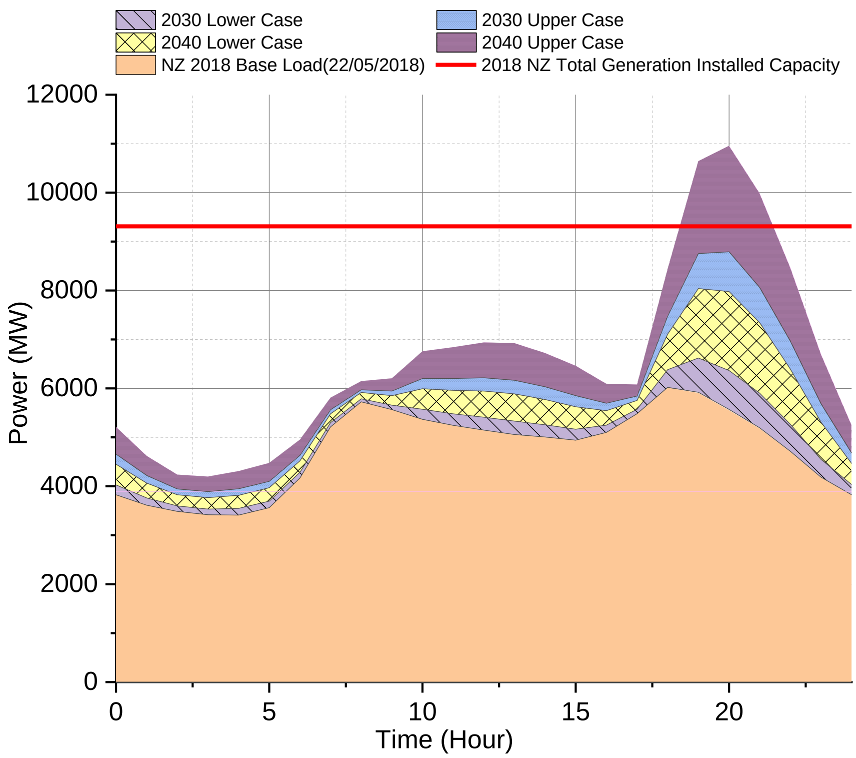


Fig. 13 Indicated Charging load profile of future EV uptakes

Fig. 13~~Fig. 13~~ exhibits the indicated 24-hour base load profile with future EV uptakes specified in Section 4. Without consideration of the base load growth, the lack of demand-side management on EVs may challenge NZ national power system regarding power generation, transmission and distribution equipment, leading to peak loads from 6024MW to 10464MW. It may exceed New Zealand's total installed generation capacity of 9281MW [38].

7. Conclusions and future research

In this paper, the uncertainty problems in planning of distribution networks with integration of EVs have been addressed. The estimation of aggregated EV charging loads based on the elaborated multivariate probabilistic model is implemented in MCS, taking into account several factors that may affect the loading profiles. EV charging and driving patterns are considered in the modelling in order to present the EV charging demand closer to a realistic scenario, in which the randomness and heterogeneous characteristics have been detailed by the proposed methodology. Moreover, the evaluation of EV charging demand at the national level reveals the potential shortage of generation installed capacity in NZ based on future EV uptakes. The case study demonstrates the peak charging demands as a result from the coincidence of EV charging loads and residential loads has been mitigated by the proposed coordinated charging strategies, in which targeted EV fleets were rescheduled to flatten the load curve, so as to postpone the investment of network reinforcement.

This study has shown the EV modelling technique used for the cross-sector analysis (transport and energy sectors) regarding the temporal distribution of charging behaviours, and charging strategies. However, more research and analysis are required to justify the adoption of EVs on the spatial distribution in electrical networks, and on economic incentives in demand-side response. Future works will explore price and non-price incentives for behavioural change in the design of EV charging strategies under a smart distribution network environment. Extending the smart charging strategy into temporal, spatial and economic considerations in the distribution networks could be a focal spot for the analyses of integrated transport and power systems at the tactical and operational level.

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