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# Electric Vehicle Capacity Forecasting Model with Application to Load Levelling

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**Abstract**—There are many uncertainties associated with forecasting electric vehicle charging and discharging capacity due to the stochastic nature of human behavior surrounding usage and intermittent travel patterns. This uncertainty if unmanaged has the potential to radically change traditional load profiles. Therefore optimal capacity forecasting methods are important for large-scale electric vehicle integration in future power systems. This paper develops a capacity forecasting model considering eight particular uncertainties under three categories to overcome this issue. The model is then applied to a UK summer scenario in 2020. The results of this analysis demonstrate that the proposed model is accurate for charge and discharge prediction and a feasible basis for steady-state analysis required for large-scale electric vehicle integration.

**Index Terms**—electric vehicle (EV), capacity forecasting, uncertainty analysis, load levelling

## I. INTRODUCTION

The growing focus on the reduction of greenhouse gas emissions and global warming effects and the increased demand for fossil fuels will limit development of the power systems and transport sector. The future smart grid which includes renewable generation alongside electric vehicles (EV) has been proposed as a solution to mitigate these sustainable development issues. However, the stochastic nature of EVs charging and discharging due to unpredictable human behaviour in terms of usage, travel trends and volume of vehicles makes reliable forecasting difficult [1]. Many countries in the world are keen to promote EV provision. For example in 2020, it is estimated that there will be about 1.2 million battery electric vehicles (BEVs) and 0.35 million plug-in hybrid electric vehicles (PHEVs) in the UK [1].

At present, mostly probabilistic approaches for driving behaviour and travel patterns have been adopted for EV charging and discharging capacity forecasting [2]-[8]. Few consider time-domain variations [3]-[4], which can be used for peripheral calculations. Some studies consider only grid-to-vehicle (G2V) charging connection which is unsuitable for future power systems where large-scale EV integration may

require vehicle-to-grid (V2G) coupling in a discharge mode, to support potential smart grid energy storage [3]-[5]. Published work to date has not systematically considered all major uncertainties, with most papers examining driving behaviour and different EV charging and discharging power levels, rather than the inclusion of additional factors, which directly affect EV viability [5]-[6]. In particular, since EV travel can be regarded as either 'normal' or 'irregular' [9], charging and discharging must be flexible, meaning that once an EV is plugged-in, charging or discharging should commence immediately.

This paper considers pertinent and timely issues, which affect both EV charging and discharging. A general model for accurate capacity forecasting is proposed and applied. The paper is organized as follows: Section II develops the EV capacity forecasting model with eight uncertainties under three categories. Section III discusses the influence of those eight uncertainties in a typical EV load levelling application. Section IV is a case study of the UK in 2020 involving load levelling. Section V presents the conclusions.

## II. EV CAPACITY FORECASTING MODEL

Capacity forecasting for EVs develops an accurate profile for scheduling charging and discharging. A typical outcome should specify a number of charging and discharging EVs over a set time interval, as well as calculating charging/discharging power levels. In this paper, the following three assumptions have been made to accurately model uncertainties in EV capacity forecasting,

- 1) The lifetime of EV batteries is assumed to be sufficient for frequent charging/discharging based on recent advances in battery technologies;
- 2) A change from charge-to-discharge mode, and vice versa, and between each time interval is considered as a step change;
- 3) The proposed charging and discharging strategy in the capacity forecasting model is designed for future power grids.

In this model, the eight uncertainties for capacity forecasting are grouped into three categories: *determinate*, *probable* and *structural* and discussed in relation to future power systems.

#### A. Determinate Uncertainties

There are four uncertainties under this category. Determination means that such uncertainties can be measured based on statistics and default parameters. In this category, the type of EV used is determined from statistical data, while the other three uncertainties are from obtained default parameters.

##### 1) Different EV types

An EV type usually refers to BEVs, PHEVs or fuel cell vehicles (FCVs). Thus, the total EV number is,

$$N = N_B + N_H + N_{FC} \quad (1)$$

where  $N_B$  is the number of BEVs,  $N_H$  is the number of PHEVs (as well as hybrid electric vehicles, HEVs) and  $N_{FC}$  is the number of FCVs.

##### 2) Charging and discharging power levels

A typical charging process is described by (2) below, where  $P_r$  is the constant charging power. The charging process commences at a constant level. Once the state of charge (SOC) reaches a certain level, it changes to constant voltage charging until full charged. Typical charging levels are available in [10]-[12].

$$P_c(t) = \begin{cases} P_r & 0 < t \leq T_1 \\ P_r \cdot (T_2 - t) / (T_2 - T_1) & T_1 \leq t \leq T_2 \end{cases} \quad (2)$$

In current conventions, EV discharging is decided in two ways: 1) Charging is the same as discharging, only in a different direction; 2) One specified EV vehicle or fleet of vehicles is used to determine a certain discharging level. In this model, the first convention has been adopted. Therefore with reference to the charging power and battery constraints, the discharging power is,

$$P_{rd} \leq \min\{P_r, P_{Bd}\} \quad (3)$$

where,  $P_{Bd}$  refers to the battery-rated discharging power.

##### 3) Available time duration

The available time duration  $T_a$  refers to the total (connected) period when charging or discharging is available for system dispatch.

$$T_{a\min} \leq T_a \leq T_{a\max} \quad (4)$$

where  $T_{a\min}$  and  $T_{a\max}$  are the minimum and maximum value for  $T_a$ . The symbol conventions used in this paper are based on published sources; typical data is listed in [5].

##### 4) Discrete accuracy

To facilitate numerical calculation, the continuous EV charging/discharging power is segmented into discrete predefined time intervals. In this model, an hour or half-hour

interval is set for steady-state analysis. The discrete charging/discharging power  $P_j$  for the  $j$  th period is,

$$P_j = \int_{(j-1)T}^{jT} P(t)/T dt, \quad 1 \leq j \leq N_c, \quad T = 24/N_d \quad (5)$$

using,

$$N_c = [T_2] \text{ is rounded up to the nearest hour for charging and} \\ N_c = [T_3] \text{ is rounded up to nearest hour for discharging}$$

where,  $N_d$  is the number of equal time periods over one day which determines the time interval  $T$  for the discretization of the charging/discharging profile and  $N_c$  is the number of the time intervals of the charging and discharging process.  $T_3$  is the discharging end time.

#### B. Probable Uncertainties

There are three uncertainties in this category. Probability means that probability distribution functions (PDF) are used to describe the uncertainties.

##### 5) Driving behaviour and travel patterns

Driving behaviour and travel patterns are applied to describe human convention in EV usage. Driving behaviour is described by the SOC and travel patterns are described by daily travel distances, obtained from published statistics [13]. The relationship between driving behaviour and travel distance is  $E = 1 - d/d_R$ , when the SOC is assumed to drop linearly with the distance, where  $E$  is the SOC,  $d$  is the daily travel distance and  $d_R$  is the maximum range of EV. Therefore the PDF of battery SOC after one day travel is [5],

$$h(E; \mu, \sigma) = \frac{1}{d_R(1-E)\sqrt{2\pi}\sigma} \times e^{-[\ln(1-E) + \ln(d_R) - \mu]^2 / (2\sigma^2)} \quad (6)$$

where  $\mu$  is the  $\log_e$  mean and  $\sigma$  is the standard deviation of the corresponding daily travel distance probability density distribution,  $0 < E < 1$ .

##### 6) Available capacity

Available capacity is relevant in a discharging mode. It is usually determined by driver behaviour and establishes two extremes, the start and end capacity points. These two points are usually described by the SOC. Thus,

$$E_a \leq E_{start} - E_{end} \\ P_d = \begin{cases} P_{rd} & 0 < t \leq T_3 \\ 0 & t > T_3 \end{cases} \quad (7)$$

where,  $E_{start}$  and  $E_{end}$  are the start point and end point SOC, respectively.

##### 7) Charging and discharging behaviour

It is apparent that not every EV participates in regular or daily G2V or V2G connection. Such EVs get charged after a certain SOC level and the number of such EVs is  $N_p$  and their charging cycle is  $CT_p$ . Other EVs may participate in G2V and/or V2G every day and the number of such EVs is  $N_a$ .

According to (5) above, the discrete SOC  $E_{cj}$  before charging starts in each time interval and  $E_{dj}$  before discharging starts (in each time interval) can be obtained. The charging/discharging power at time  $l$  for the above two types of EVs is discussed below.

a) *Charging-only EV*

Assuming that the charging start time and the initial SOC are two independent variables, the probability of a battery starting charge at time  $k$ , and operating at power level  $P_{cj}$  at later time  $l$  can be expressed as,

$$\begin{aligned} \varphi(P_{cj}, l) &= \sum_{k=1}^l f(k)h(E_{cj} - \sum_{i=1}^m E_{ci}) \\ N_c \leq l \leq N_d, m &= l - k < j \\ E_k &\leq E_{c\_set} \end{aligned} \quad (8)$$

where,  $f(k)$  is the probability of a charging process starting at time  $k$  and  $h(E_j - \sum_{i=1}^m E_{ci})$  is the probability of an initial battery SOC from which the EV starts charging at power level  $P_{cj}$ .  $E_k$  is the SOC at start time and  $E_{c\_set}$  is the set value of the start SOC for charging-only EVs. The charging power of  $N_p$  EVs at time  $l$  is given as,

$$P_p(l) = N_p \sum_{j=1}^{N_c} P_{cj} \varphi(P_{cj}, l) \quad (9)$$

b) *Flexible EV*

Flexible EVs are assumed to charge/discharge frequently every day and the battery lifetime is sufficient to support this routine. Assuming that flexible charging/discharging starts at time  $k$ , the SOC at a later time  $l$  after  $m$  intervals charging and  $n$  intervals discharging is as follows,

$$\begin{aligned} E_l &= E_k + \sum_{i=1}^m E_{ci} - \sum_{i=1}^n E_{di} \\ 0 \leq m, n < T_a, N_c < l < T_a, m + n < l - k < j \end{aligned} \quad (10)$$

Here, it is assumed that charging and discharging are calculated in discrete time intervals and continuous or taken by turns to obtain flexibility.

Four scenarios are proposed for flexible EV charging/discharging: a. Start charge at time  $k$  and charge at power level  $P_{cj}$  at later time  $l$ ; b. Start charge at time  $k$  and discharge at power level  $P_{dj}$  at later time  $l$ ; c. Start discharge at time  $k$  and charge at power level  $P_{cj}$  at later time  $l$ ; d. Start discharge at time  $k$  and discharge at power level  $P_{dj}$  at later time  $l$ .

There are  $m$  charging intervals and  $n$  discharging intervals between the start time  $k$  and later time  $l$ . The probability of these four scenarios can be expressed as,

$$\begin{cases} \alpha(P_{cj}, l) = \sum_{k=1}^l f(k)h(E_{cj} - (\sum_{i=1}^m E_{ci} - \sum_{i=1}^n E_{di})) \\ \beta(P_{dj}, l) = \sum_{k=1}^l f(k)h(E_{dj} - (\sum_{i=1}^m E_{ci} - \sum_{i=1}^n E_{di})) \\ \gamma(P_{cj}, l) = \sum_{k=1}^l g(k)h(E_{cj} - (\sum_{i=1}^m E_{ci} - \sum_{i=1}^n E_{di})) \\ \phi(P_{dj}, l) = \sum_{k=1}^l g(k)h(E_{dj} - (\sum_{i=1}^m E_{ci} - \sum_{i=1}^n E_{di})) \end{cases} \quad (11)$$

where,  $g(k)$  is the probability of a discharging process starting at time  $k$ . It is obvious that when  $m=0$  or  $n=0$  there is only charging or discharging between the start time  $k$  and later time  $l$ , or it just starts at time  $l$ .

Assuming the number of EVs in each scenario, charging/discharging start time and initial SOC are independent variables and discharging is in effect negative charging, the probability of charging power of  $N_a$  EVs at time  $l$  is given as,

$$\begin{aligned} P_a(l) &= N_\alpha \sum_{j=1}^{N_c} P_{cj} \alpha(P_{cj}, l) - N_\beta \sum_{j=1}^{N_c} P_{dj} \beta(P_{dj}, l) \\ &+ N_\gamma \sum_{j=1}^{N_c} P_{cj} \gamma(P_{cj}, l) - N_\phi \sum_{j=1}^{N_c} P_{dj} \phi(P_{dj}, l) \\ N_\alpha + N_\beta + N_\gamma + N_\phi &= N_a \end{aligned} \quad (12)$$

The total charging power at time  $l$  is given as,

$$P_{EV}(l) = P_p(l) / CT_p + P_a(l) \quad (13)$$

C. *Structural Uncertainties*

The only uncertainty in this category is residential load. Structure means that such uncertainties can be affected by external electric power networks at the connection node of EV station.

8) *Residential loads*

A conventional distribution grid is normally designed for consumer connection. Therefore, in EV charging, the total load is extended. In EV discharging, the EV discharging connection point and the magnitude of discharging power should be identified since it is the reverse direction of traditional power flow. This uncertainty has a great influence on the power flow distribution calculation and also the EV station placement and sizing. However, this uncertainty can be ignored in power balancing or load levelling issues since an equivalent load is assumed.

Equation (1)-(13) therefore describe a flexible EV capacity forecasting model.

III. UNCERTAINTY ANALYSIS IN LOAD LEVELLING

Load levelling is one of the typical technical applications of large-scale EVs. In this paper, a classic view of a flat load profile is adopted.

A. *Optimization model*

The system power demand  $P_s$  consists of two parts as,

$$P_S(l) = P_{EV}(l) + P_L(l) \quad (14)$$

where,  $P_{EV}(l)$  is the total EV charging demand at time  $l$ , and  $P_L(l)$  is the gross demand without EVs at time  $l$ . In larger systems, the system demand (14) needs to be modified since network loss and EV siting and sizing need to be considered.

The optimization problem is hence concluded as follows,

$$\min z = \frac{1}{N_d} \sum_{l=1}^{N_d} (P_S(l) - \bar{P}_S)^2 = \frac{1}{N_d} \sum_{l=1}^{N_d} P_S(l)^2 - \bar{P}_S^2 \quad (15)$$

where,  $\bar{P}_S$  is the average demand. Since this is a constant and it does not affect the minimization, the second term in (14) can be ignored. Substituting (1)-(14) into (15), the problem can then be reformulated as follows,

$$\begin{aligned} \min z &= \sum_{l=1}^{N_d} P_S(l)^2 = \sum_{l=1}^{N_d} (P_p / CT_p + P_a + P_L(l))^2 \\ \text{s.t.} &\begin{cases} \sum f(l) + \sum g(l) = 1 \\ f(l) \geq 0, g(l) \geq 0, \forall t \in [1, N_d] \end{cases} \end{aligned} \quad (16)$$

where,  $z$  is the objective function and  $f(l)$  and  $g(l)$  are the decision variables which are the percentage of EVs that start charging and discharging at time  $l$ .

Equation (16) is a quadratic programming problem, which can then be solved by sequential quadratic programming (SQP) which in this work was performed in MATLAB [7].

### B. Uncertainty analysis

In uncertainty analysis, each uncertainty is considered separately, while all other uncertainties are set as constants. Several other uncertainties are not discussed in this paper due to restrictions in scope and paper length, but these were obtained as constants from published statistics and default parameters in the UK (2020) forecast used in the case study [1]. Thus, only the *charging and discharging power levels* and *charging and discharging behaviour* are detailed.

#### 1) Charging and discharging power levels

From (9), (12) and (13) it is apparent that,

$$\begin{aligned} P_{EV}(l) &= P_p(l) / CT_p + P_a(l) \\ &= P_c(l)\Theta_p(l) + P_c(l)\Theta_\alpha(l) - P_d(l)\Theta_\beta(l) \\ &\quad + P_c(l)\Theta_\gamma(l) - P_d(l)\Theta_\theta(l) \\ &= P_c(l)\Theta_c(l) - P_d(l)\Theta_d(l) \end{aligned} \quad (17)$$

where  $\Theta(l)$  are the products of EV numbers and probabilities at time  $l$  in each scenario. According to the description of charging and discharging power levels, it can be seen that when  $\Theta(l)$  is constant, with higher charging or discharging power levels, the total EV charging or discharging power  $P_{EV}(l)$  is larger, and vice versa. However, EV numbers at each time interval are achieved by the optimization solution. When the initial SOC is determined,  $P_{EV}(l)$  will be approximately the same at each time interval due to constant battery energy capacity and this uncertainty will have no influence on the load levelling results.

#### 2) Charging and discharging behaviour

Charging-only EVs have individual and periodic variations. With large-scale EV integration, the demand from charging-only EVs can be regarded as a smooth base-load, which has little or no effect on load levelling. However, with a larger proportion of flexible EVs, better load levelling results can be achieved.

## IV. CASE STUDY

### A. Parameters

A UK 2020 summer scenario is selected for this case study. Parameters in the case study are listed in Table I [1, 5, 12]. Power system demand normally shows periodic variations over 24 hours. Based on the historical data from 2004-2012 [14], and taking into consideration improvements in energy efficiency and Gone Green scenarios [15], the daily profile of UK (national summer demand) in 2020 is predicted as shown in Figure 1. Here the gross demand includes embedded solar and wind energy and excludes EVs.

TABLE I. LIST OF PARAMETERS

Symbols	Values	Symbols	Values
$N_B$	1.2 million	$N_H$	0.35 million
$P_c, P_{rd}$	7 kW	$T_1$	3.2 <sup>a</sup> , 0.64 <sup>b</sup>
$T_2$	4 <sup>a</sup> , 0.8 <sup>b</sup>	$T_3$	1.8 <sup>a</sup> , 0.36 <sup>b</sup>
$T_{a\min}$	0	$T_{a\max}$	47
$N_d$	48	$\mu$	3.20
$\sigma$	0.6528	$E_{end}$	0.5
$E_{c\_set}$	0.3	$CT_p$	2.9

a. For BEVs with 25 kWh lithium-ion battery; b. For PHEVs with 5 kWh lithium-ion battery

### B. Results

The proportion of charging-only EVs and flexible EVs are considered in three scenarios: 1) 80% charging-only EVs and 20% flexible EVs; 2) 50% charging-only EVs and 50% flexible EVs; and 3) 20% charging-only EVs and 80% flexible EVs. The results obtained are shown in Fig. 1. The numerical calculation time for the model is approximately 4 seconds, running on a PC with Intel® Core™ 2 Duo CPU E8500 and 4 GB RAM.

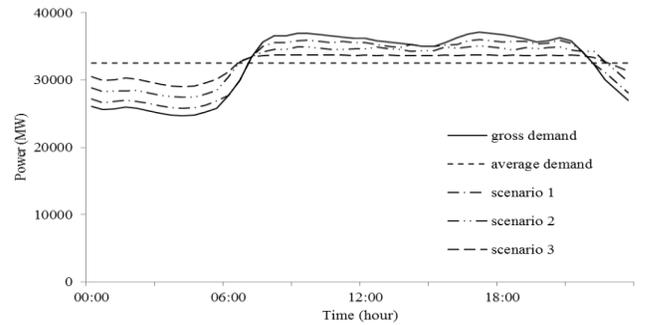


Figure 1. Load levelling results with different proportions of EVs

From Fig. 1 it is apparent that a larger proportion of flexible EVs are more effective in facilitating load levelling.

This is because charging-only EVs charge regularly with a periodic variation of 2.9 days. Taking into consideration large-scale EV integration, charging-only EVs can be regarded as smooth base load, which has little effect on load levelling. It is expected that in all three scenarios, a higher number of EVs (that used in this study) could render a profile closer to the flat line in Fig. 1.

Assuming a proportion of 20% charging-only EVs and 80% flexible EVs, different charging and discharging levels in [15] are applied in the simulation and the results are shown in Figure 2.

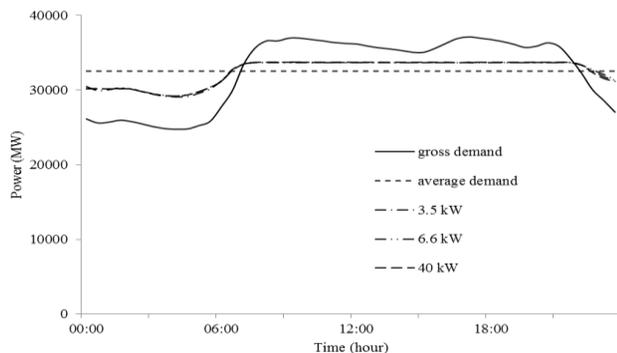


Figure 2. Load levelling results with different power levels

From Fig. 2 the results are roughly similar in the different charging and discharging power levels due to identical battery energy capacity. There are slight differences between different power levels since the product of numbers of EVs and their power levels are not strictly equivalent. The results are also different from previous studies [7], [9] because of inclusion of the flexible EV capacity forecasting model. In the proposed model, charging and discharging can either be continuous or occur alternately to achieve flexibility.

In this case, both peak-shaving and valley-filling can be achieved by EV discharging and charging. The proposed EV capacity forecasting model is therefore effective and can be used in steady-state analysis with large-scale EV integration.

## V. CONCLUSIONS

This paper initially develops a flexible EV capacity forecasting model. Eight uncertainties in three categories are taken into consideration. Discharging is assumed as negative charging and an EV battery is assumed to be a sustainable resource for frequent and flexible charging and discharging. Flexibility means that charging or discharging is continuous or occurs alternately. The proposed model has been applied in load levelling and the influence of uncertainties discussed. From an application to load levelling, using a forecast of EV usage in the UK (by 2020), the results demonstrate that a larger proportion of flexible EVs renders a greater impact on load levelling. Different charging and discharging power levels result in roughly the same results due to the similar battery energy capacities. Based on the work reported in this paper, it is apparent that EV charging and discharging can be accurately determined using the proposed model, with particular application to steady-state analysis of power

systems which include large-scale EV integration. The next steps in the work will enhance and fine tune the model further to include better structural load forecasting for residential loads [16] and larger systems; take account of variable renewable energy [17] and weather impacts on modal choice and battery performance [18]; and study computational efficiency.

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