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The Impact of Electric Vehicle Uncertainties on Load Levelling in the UK

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***Abstract*—Electric vehicles (EVs) integration in modern power systems has modified the nature of traditional power demand, which brings uncertainties in the energy consumption end. Such uncertainties may lead to a variety of influences on the performance of EV applications in power systems. This paper focuses on the EV application to load levelling in the UK. Six EV uncertainties are specified to analyze the impact on three parameters, which describe the performance of load levelling. The UK EV and power system data are used in the case study. The simulation results show that the battery sizes, discrete accuracy, and driving behavior have little influence on the load levelling results; a better load levelling result can be obtained with larger EV scales, larger discharging available capacity, and longer available time duration; inappropriate selection of available time duration may worsen the ramps, which bring challenges to conventional generators.**

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

I. INTRODUCTION

As a promising solution to fossil fuel shortage and environmental concerns, electric vehicles (EVs) have drawn more and more attention in both transportation and electricity sectors. Many countries have published their EV goals since 2000s [1-5]. Unfortunately however, such EV goals seem not to be achieved by the desired years. The USA Department of Energy predicted in 2010 that approximately 1 million plug-in hybrid electric vehicles (PHEVs)/EVs will be on the road by 2015 and 425,000 PHEVs/PEVs will be sold in 2015 alone [2]. According to the monthly sale records, by the end of 2015, there were 116,099 EV sales in the USA, which was only a quarter of its original projection [3]. The total EV number was only about 408,000 by 2015, which was roughly 40% of its ambition. The UK published its EV goals in 2008 with 1.2 million battery electric vehicles (BEV) and 0.35 million PHEVs by 2020; and, 3.3 million BEVs and 7.9 million PHEVs by 2030 [4]. By the end of 2015, there were 50,421 EVs registered in the UK [5]. An optimistic prediction, published in 2016, indicates that there will be about 0.7 million EVs [5] in the UK by 2020, which is about half of its original projection. It is also estimated that the total number of EVs will be around 5.8 million by 2030 [5].

The slower EV uptake is mainly due to two reasons. Firstly, the EV battery is not large enough or efficient enough for users to overcome the "range anxiety". At present, the top three popular EVs are Tesla Model S, Nissan Leaf, and Chevrolet Volt [3]. Volt is a PHEV and thus with less range anxiety. Model S is with the largest battery capacity (85 kWh) for current commercial EVs. The maximum range is 300 miles, which is enough for most journeys. Leaf can be regarded as a representative of many other commercial BEVs. It is with a battery capacity of 24 kWh and a range of 100 miles. Many users consider such range is not able to fulfill daily long journey use. However, it is hardly to be improved unless revolutionary battery technologies emerge [6]. The other reason is the stochastic and intermittent characteristics of EV [7-9]. Such characteristics (uncertainties) directly affect the EV charging and discharging power at a specific time period, making large-scale EV integration in power systems challengeable, and thus, limiting the overall uptake of EVs in a modern society. Previous studies [7-9] introduced nine uncertainties in three categories, including EV scales, battery sizes, power levels, available time duration, discrete accuracy, driving behavior, discharging available capacity, charging/discharging behavior and residential loads. To study the impact of EV uncertainties is to examine the influence of parameter variations of each uncertainty on the performance of various EV applications.

According to the discussion in [1] and [7], the EV technical benefits include the application in load levelling [8-9], renewable energy support [7, 10], tie-line regulation [7, 11], unit commitment [12-13], economic dispatch [14-15], frequency regulation [16-17], power oscillation stabilizer and shock absorber [18-19] etc., among which, load levelling is the most popular one to illustrate the EV advantages. In load levelling, all above uncertainties except residential loads should be included [8]. Three parameters are usually used to describe the performance of load levelling, such as peak demand, peak-valley difference, and maximum ramp. All these three parameters are cost attributes, meaning that the smaller, the better. Usually, the positive ramp (ramp-up rate) is of more interests than the negative ramp (ramp-down rate).

This paper is an elaboration and extension of previous studies [7-9]. It tries to analyze the impact of EV uncertainties on the performance of load levelling results. UK EV data, vehicle travel data, power system data are used to demonstrate the impacts. The remaining of the paper is organized as follows. Section II demonstrates the definitions of each uncertainty and the variation range in uncertainty analysis. Section III introduces the data sources used in the case studies in Section IV. Section V presents the conclusions and future work of this paper.

II. DEFINITION AND THE VARIATION RANGE OF EACH UNCERTAINTY

The influence of different power levels and charging/discharging behavior on load levelling results has been analyzed in previous study [8]. Thus, they are not discussed in this paper.

A. EV scales

EV scales describe the numbers of different EV types (models) or EV market share. At present, EVs mainly refer to BEVs, PHEVs and Range Extended Vehicles (REVs). There are also limited commercial Fuel Cell Vehicles (FCVs), which include the Hyundai ix35 FCEV (Tucson FCEV) and Toyota Mirai (Japanese for "future"). In 2015, the EV market shares of seven countries surpass 1% level, which are Norway, the Netherlands, Sweden, Denmark, France, China and the United Kingdom. Market shares reached 23% in Norway and nearly 10% in the Netherlands [6].In this paper, the EV scales refer to the numbers of BEVs and PHEVs. The number as 2 and 4 times of UK 2020 scale are used in this analysis.

B. Battery sizes

Battery sizes refer to the energy capacity of EVs. Taking into account the initial state-of-charge (SOC) and battery sizes, the daily energy demand to fully charge all EVs can be obtained. In Europe, it is recommended that the battery size for a BEV is in the range of 20-30 kWh and for a PHEV, 5-15 kWh [20]. According to the UK vehicle statistics [21], EV numbers of current models can be obtained, and thus, the battery sizes can be obtained. Since the UK is predicted to be with more PHEVs than BEVs in 2016-2020 [5-6] but the BEV's battery size is much larger than PHEV's, half of the future EVs are considered as BEVs. BEVs, with size ranging from 20-50 kWh are used to demonstrate this uncertainty.

C. Available time duration

Available time duration refers to the duration when EVs are available for charging and discharging management. It has been widely recognized that irregular charging might aggravate system loading at peak time. Inappropriate selection of available time duration may also worsen the system loading. For example, if the available time duration is only set as 17:00-23:00, which is the load peak period in the UK, the charging demand will be added to the load peaks, which should be avoided. In this paper, the available time duration is set as daytime (6:00-18:00), night (18:00-6:00), and all day.

D. Discrete accuracy

EV charging and discharging management is organized as discrete optimization. The discrete accuracy is defined as the discrete time slots, such as 1 hour, half hour, 15 minutes etc. It determines the dimensions of the decision variables of the optimization problem. In addition, Since EVs are usually assumed to be fully charged at the end of the calculation period and the total required energy is calculated by the discrete initial SOC and the battery capacity, shorter time slots (higher discrete accuracy) will result in more precise results. In this paper, 1 hour, half hour and 15 minutes are selected to demonstrate this uncertainty.

E. Driving behavior

Based on previous studies, this uncertainty describes the probability of the initial SOC [7-9]. In this study, log-normal distribution is adopted to describe the probability density function (pdf) as shown in (1).

$$h(E;\mu,\sigma)=\frac{1}{d_R(1-E)\sqrt{2\pi}\sigma}\times e^{-\left[\ln(1-E)+\ln(d_R)-\mu\right]^2/\left(2\sigma^2\right)} \qquad (1)$$
$$0<E<1$$

where μ is the $\log_e$ mean and σ is the standard deviation of the corresponding daily travel distance pdf. E is the initial SOC after one day travel and d_R is the daily maximum travel distance. The daily required energy to fully charge all EVs can be calculated as the integral of the pdf h with respect to E from 1 to 0. Thus, by calculating the integral and changing the upper and lower limits and assuming $x=\left[\ln(1-E)+\ln(d_R)-\mu\right]/\sigma$, the integral of (1) can be rewritten as,

$$W=\int_1^0 h\mathrm{d}E=\int_{-\infty}^{\left[\ln(d_R)-\mu\right]/\sigma}\frac{1}{\sqrt{2\pi}}\times e^{-x^2/2}\mathrm{d}x \qquad (2)$$

Equation (2) is a definite integral of standard normal distribution form negative infinite to $\left[\ln(d_R)-\mu\right]/\sigma$. The magnitude is determined by $\left[\ln\left(d_R\right)-\mu\right]/\sigma$. Therefore, the required energy is a function with respect to μ and σ, which can be expressed as $f\left(\mu,\sigma\right)=\left[\ln\left(d_R\right)-\mu\right]/\sigma$. Based on the partial differential of $f\left(\mu,\sigma\right)$ with respect to μ and σ, it can be obtained that the required energy decreases with the increase of μ and σ. In this paper, μ and σ in 2020 are forecasted and considered in the case study. Small variations of each parameter are analyzed.

F. Discharging available capacity

Discharging available capacity is described by setting the discharging end SOC. Such SOC can be determined by the EV users. It stands for the least energy capacity for the next journey. In this paper, it is set as 0.4, 0.5, and 0.6 for uncertainty analysis, which means discharging available capacity of 60%, 50%, and 40%, respectively.

III. DATA SOURCES

The UK EV, vehicle, and power system data are used in this study. The UK Vehicle Statistics by June 2016 [21] is used to calculate the energy capacity of current EVs; the UK National Travel Survey [22] is used to calculate the pdf of daily travel distance (initial SOC); the Gone Green Scenario in the UK Future Energy Scenarios [5] is used to obtain the future EV numbers and peak demand in 2020; taking into account the daily load profile in a winter-maximum scenario [23-24], the load profile in 2020 is obtained; the EV charging power levels from IEC standard [25] are considered for standard charging (7 kW), fast charging (22 kW) and rapid charging (50 kW), respectively.

IV. CASE STUDY

A. Simulation funcitons and parameters

By considering a classic flat load profile, the optimization function of load levelling can be expressed as follows,

$$\begin{aligned}
&P_S\left(l\right)=P_{EV}\left(l\right)+P_L\left(l\right)\\
&\min z=\frac{1}{N_d}\sum_{l=1}^{N_d}\left(P_S\left(l\right)-\bar{P}_S\right)^2\\
&\quad=\frac{1}{N_d}\sum_{l=1}^{N_d}P_S\left(l\right)^2-\bar{P}_S^{\,2}\\
&\quad=\sum_{l=1}^{N_d}P_S\left(l\right)^2\\
&s.t.\begin{cases}\sum f\left(l\right)+\sum g\left(l\right)=1\\ f\left(l\right)\geq 0, g\left(l\right)\geq 0, \forall l\in\left[1,N_d\right]\end{cases}
\end{aligned}\tag{3}$$

where, $P_{EV}\left(l\right)$ is the total EV charging demand at time l, $P_S\left(l\right)$ and $P_L\left(l\right)$ is the demand with and without EVs at time l, respectively. $\bar{P}_S$ is the average demand. N_d is the number of equal time periods over one day which determines the time interval for the discretization of the charging/discharging profile. z is the objective function and $f\left(l\right)$ and $g\left(l\right)$ are the decision variables which are the percentage of EVs that start charging and discharging at time l, respectively.

Equation (3) is a quadratic programming problem, which can then be solved by sequential quadratic programming (SQP) which in this work was performed in MATLAB. The detailed optimization function and the solving algorithms [26] can be found in [7-9].

The peak demand, peak-valley difference, and the maximum ramps with and without EVs can be obtained by (4) and (5) respectively.

$$\begin{cases}
P_{S_P}=\max\limits_{l}\left\{P_S\left(l\right)\right\}\\
P_{S_PVD}=\max\limits_{l}\left\{P_S\left(l\right)\right\}-\min\limits_{l}\left\{P_S\left(l\right)\right\}\\
P_{S_MR}=\begin{cases}\max\limits_{l}\left\{P_{S_r}\left(l\right)\right\}*N_d/24 & \text{positive ramp}\\ \min\limits_{l}\left\{P_{S_r}\left(l\right)\right\}*N_d/24 & \text{negative ramp}\end{cases}\\
P_{S_r}\left(l\right)=\begin{cases}P_S\left(1\right)-P_{S-1}\left(N_d\right) & l=1\\ P_S\left(l\right)-P_S\left(l-1\right) & 1<l\leq N_d\end{cases}\\
\forall l\in\left[1,N_d\right]
\end{cases}\tag{4}$$

$$\begin{cases}
P_{L_P}=\max\limits_{l}\left\{P_L\left(l\right)\right\}\\
P_{L_PVD}=\max\limits_{l}\left\{P_L\left(l\right)\right\}-\min\limits_{l}\left\{P_L\left(l\right)\right\}\\
P_{L_MR}=\begin{cases}\max\limits_{l}\left\{P_{L_r}\left(l\right)\right\}*N_d/24 & \text{positive ramp}\\ \min\limits_{l}\left\{P_{L_r}\left(l\right)\right\}*N_d/24 & \text{negative ramp}\end{cases}\\
P_{L_r}\left(l\right)=\begin{cases}P_L\left(1\right)-P_{L-1}\left(N_d\right) & l=1\\ P_L\left(l\right)-P_L\left(l-1\right) & 1<l\leq N_d\end{cases}\\
\forall l\in\left[1,N_d\right]
\end{cases}\tag{5}$$

where, P_{S_P} and P_{L_P} are the peak demands, P_{S_PVD} and P_{L_PVD} are the peak-valley differences, P_{S_MR} and P_{L_MR} are the maximum ramps, $P_{S\_r}\left(l\right)$ and $P_{L\_r}\left(l\right)$ are the ramping rates between adjacent time intervals, $P_{S-1}\left(N_d\right)$ and $P_{L-1}\left(N_d\right)$ are the demands at time N_d in previous day. Subscript S stands for the scenario with EVs, and L stands for the scenario without EVs.

UK 2020 winter-maximum scenario is considered in this study. The parameters are shown in Table I and the load profile without EVs integration is shown in Figure 1.

TABLE I. LIST OF PARAMETERS

Items	Values
EV number	696,246
Charging and discharging power level	7 kW
Time for constant power charging/Time for fully charge a 20 kW BEV	2.5 h/3 h

Time for constant power charging/Time for fully charge a 25 kW BEV	3 h/4 h
Time for constant power charging/Time for fully charge a 50 kW BEV	7 h/7.5 h
Time for constant power charging/Time for fully charge a 5 kW PHEV	0.5 h/1 h
Default BEV/PHEV battery size	25 kWh/5 kWh
Default available time duration	24 h
Default N_d	48
Default μ	3.2125
Default σ	0.6537
Default discharging end SOC	0.1
Percentage of flexible EVs [7-8]	100%

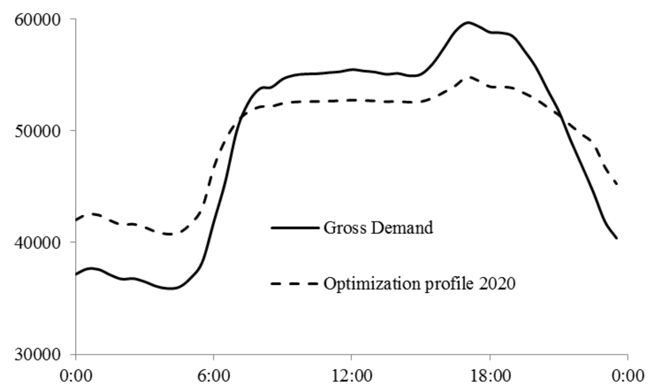

Figure 1. Load profile of the UK 2020 winter-maximum scenario

B. *Simulation results*

Due to page limits, the graphic load levelling results (figures) are not listed in this paper. Figure 1 presents the optimization load profile with EV integration under default parameters of the proposed uncertainties in [7-8]. The peak demand, peak-valley difference, and the maximum ramps in 2020 under different uncertainties are calculated in this paper. The detailed simulation results are shown in Table II-VII.

TABLE II. VARIATION AND RESULTS OF EV SCALES

EV scales	Peak demand (MW)	Peak-valley difference (MW)	Maximum ramp (MW/h)
No EV	59,700	23,809	9,150/-6,472
696,246	54,826	14,062	7,166/-6,472
1,392,492	50,460	4,822	4,896/-6,472
2,784,984	49,706	0.001	0.002/-0.001

TABLE III. VARIATION AND RESULTS OF BATTERY SIZES

Battery sizes	Peak demand (MW)	Peak-valley difference (MW)	Maximum ramp (MW/h)
No EV	59,700	23,809	9,150/-6,472
20 kWh	54,826	14,062	7,166/-6,472
25 kWh	54,826	14,062	7,166/-6,472
50 kWh	54,826	14,062	7,166/-6,472

TABLE IV. VARIATION AND RESULTS OF AVAILABLE TIME DURATION

Available time duration	Peak demand (MW)	Peak-valley difference (MW)	Maximum ramp (MW/h)
No EV	59,700	23,809	9,150/-6,472
daytime	58,847	22,956	16,913/-6,472
night	59,700	18,935	9,668/-10,813
All day	54,826	14,062	7,166/-6,472

TABLE V. VARIATION AND RESULTS OF DISCRETE ACCURACY

Time slot	Peak demand (MW)	Peak-valley difference (MW)	Maximum ramp (MW/h)
No EV	59,700	23,809	9,150/-6,472
15 min	54,826	14,062	7,166/-6,472
30 min	54,826	14,062	7,166/-6,472
60 min	54,826	14,062	7,166/-6,472

TABLE VI. VARIATION AND RESULTS OF DRIVING BEHAVIOR

μ	σ	Peak demand (MW)	Peak-valley difference (MW)	Maximum ramp (MW/h)
No EV		59,700	23,809	9,150/-6,472
3.2125	0.6537	54,826	14,062	7,166/-6,472
3	0.6537	54,826	14,062	7,166/-6,472
3.5	0.6537	54,826	14,062	7,166/-6,472
3.2125	0.6	54,826	14,062	7,166/-6,472
3.2125	0.7	54,826	14,062	7,166/-6,472

TABLE VII. VARIATION AND RESULTS OF DISCHARGING AVAILABLE CAPACITY

Discharging end SOC	Peak demand (MW)	Peak-valley difference (MW)	Maximum ramp (MW/h)
No EV	59,700	23,809	9,150/-6,472
0.4	56,776	16,011	5,178/-4,616
0.5	57,263	16,498	5,481/-3,877
0.6	57,751	17,463	5,928/-4,193

From Table II, IV and VII it can be obtained that the EV scales, available time duration, and discharging available capacity are of great impact on the load levelling results. The peak demands, peak-valley differences, and maximum ramps decrease with the increase of EV scales. The load levelling results are different with different selection of available time duration. Longer available time duration results in a better load profile. However, inappropriate selection of available time duration will worsen the ramps which bring challenges to conventional generators. For example, if daytime (6:00-18:00) is set as available time duration, the maximum ramp ascends 84.8% of that without EVs. By introducing a larger discharging available capacity, meaning that with smaller discharging end SOC, the peak demand, peak-valley difference and maximum ramp are all reduced.

From Table III, V, and VI it can be seen that the variations of battery sizes, discrete accuracy and driving behavior have little influence on the load levelling results. The simulation results remain the same with different parameters. This is due to the huge original values of peak demands, peak-valley differences and maximum ramps. EV charging and discharging powers are not able to mitigate the influences of such values. Although the results are the same, the specific EV charging demands at different time slots vary. For example, the EV demands at 21:30 for the latter three rows of Table III and V, and the latter four rows of Table VI are 1,349, 1,322, 1,290, 1,290, 1,322, 1,410, 1,340, 1,293, 1,330, and 1,315 MW.

Therefore, it is summarized that, higher EV penetration, larger discharging available capacity, and longer available time duration, especially during light loading periods, are more efficient to improve the load profile with less fluctuation and slower ramping. In this paper, the uncertainty analysis focuses on the variation of single-uncertainty. The impact of the variations of multi-uncertainties will be part of future work.

V. Conclusions

This paper analyzes the impact of EV uncertainties on the performance of EV application to load levelling in the UK, based on the authors' previous work. The uncertainties include: EV scales, battery sizes, available time duration, discrete accuracy, driving behavior and discharging available capacity. The UK vehicle statistics, travel survey, EV data, power system capacity and standard EV charging power levels are adopted in this study. The Gone Green scenario of UK 2020 power system is applied to demonstrate the impacts. The simulation results show that the battery sizes, discrete accuracy, and driving behavior have little influence on the load levelling results but the EV demands at the same time interval are different; a better load levelling result can be obtained with larger EV scales, larger discharging available capacity, and longer available time duration; inappropriate selection of available time duration will worsen the ramps which bring challenges to conventional generators.

In future studies, technical applications (load levelling, renewable energy support, etc.) in various years will be discussed, based on which, technical recommendations to power utilities will be supplied; the impact of the variations of multi-uncertainties; the impact on other issues such as environment and economic applications will be focused as well.

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