Abstract—With the increasing use of renewable energy in the Great Britain (GB) power system, the role of electric vehicles (EVs) contributes to primary frequency response was investigated. A tool was developed to estimate the EV charging load based on statistical analysis of EV type, battery capacity, maximum travel range and battery state of charge. A simplified GB power system model was used to investigate the contribution of EVs to primary frequency response. Two control modes were considered: disconnection of charging load (case I) and discharge of stored battery energy (case II). For case I, the characteristic of the EV charger was also considered. A case study shows results for the year 2020. Three EV charging strategies: “dumb” charging, “off-peak” charging, and “smart” charging, were compared. Simulation results show that utilizing EVs to stabilize the grid frequency in the GB system can significantly reduce frequency deviations. However the requirement to schedule frequency response from conventional generators is dynamic throughout the day.

Index Terms—Electric vehicles (EVs), primary frequency response, state of charge (SOC), vehicle-to-grid (V2G).

I. INTRODUCTION

A NUMBER OF countries have taken specific initiatives to de-carbonize their electrical power system and transport sectors by encouraging renewable power generation and supporting the use of plug-in battery electric vehicles (EVs). In the UK, it is anticipated that a large proportion of renewable power will come from wind turbines. There may be up to 30 GW of wind generation within a total generation capacity of some 100 GW serving a load of around 60 GW by 2020. In order to realize the target of reducing CO$_2$ emissions from the domestic transport sector by 14% by 2020, the UK Government has supported EV trials with the anticipation that EVs will play a major role in the future transport sector [1].

The uncertainties brought by the variability of renewable energy generation introduce inevitable concerns over the operation of the power system. A high penetration of renewable energy especially wind energy will increase the difficulty of frequency regulation. Several studies have already been carried out to investigate frequency control with high renewable energy penetration. Oudalov et al. [2] and Pascal et al. [3] proposed to use Battery Energy Storage Systems (BESS) for frequency regulation and developed a frequency droop controller to realize this function by reducing the generator torque set point. Short et al. [4] investigated the influence of wind turbine behaviour on primary frequency control in the Great Britain (GB) power system. Ramtharan et al. [5] assessed the ability of doubly fed induction generator wind turbines to provide frequency regulation and developed a frequency droop controller to realize this function by reducing the generator torque set point. Short et al. [6] examined the possibility of providing the required frequency response through dynamic demand control of refrigerators and a simulation study was reported that used linearly varying temperature set points with the system frequency to decide when to switch them on and off.

In recent years there has been growing interest in EVs. The introduction and widespread use of EVs could potentially lead to significant impacts on power systems [7]. In [8], a method to model EV charging load was developed and the impact of vehicle charging load on the load demand of a local distribution network was analysed. However it was assumed that all the EVs had the same battery type and the characteristics of different EV classes were not taken into consideration. As discussed in [9], the vehicle-to-grid (V2G) concept with a bidirectional power interface allows an EV to act as a mobile battery storage system for frequency regulation. Primary frequency response from EVs in a small-scale isolated power networks was investigated in [10] and [11]. A droop control was used to adjust the EV charging power according to the change of frequency.

A load estimation tool was developed to estimate the EV charging load based on statistical analysis of EV type, battery capacity, maximum travel range and battery state of charge. An
EV database created by the EU “MERGE” project [12] was used as an input to the statistical analysis. A simplified GB power system model was used and the potential contribution of EVs to primary frequency response was investigated with two control modes: disconnection of charging load and discharge of stored battery energy. A case study was undertaken for the year 2020. Results for three EV charging strategies: “dumb” charging, “off-peak” charging, and “smart” charging, were compared.

II. FREQUENCY CONTROL IN GB SYSTEM

A. Frequency Control

Frequency is controlled by balancing system demand and generation. When there is a significant power imbalance of the system, the frequency will show a large deviation. The initial rate of change is determined by the inertia of the rotating masses of the power system.

The steady state system frequency limits of the GB power system are 50 ± 0.5 Hz [13]. The GB system is designed to accept the largest credible loss of 1320 MW of generation (two of the largest generators, 2 × 660 MW) and the frequency change will be limited to −0.8 Hz with frequency restored to 49.5 Hz within 1 minute. A typical frequency transient for a generation loss of 1320 MW is shown in Fig. 1 [14], [15].

In the future, a de-carbonized GB electric power system will receive more energy from renewable sources, particularly from wind power and mainly through power electronic interfaces. The system also needs to be ready to accept a higher sudden loss of generation (up to a new maximum of 1800 MW of new very large nuclear generators that are anticipated) [16]. Therefore more primary response is likely to be required.

B. The Simplified GB Power System Model

A simplified model, shown in Fig. 2, was used to represent the GB system. This takes account of the characteristics of the generators on the system and damping provided by the frequency dependent loads. In this model synchronous power plants such as coal, gas, nuclear and hydro respond to a drop in frequency and increase their power output. These responsive synchronous plants are represented by blocks having a governor droop, a governor actuator and a turbine. The speed control of the turbines is represented by a governor droop with an equivalent gain value, $R_{eq}$, which depends on the combined effect of the droops of all generator speed governors. It operates on an input of the speed deviation formed between a reference speed and the actual speed. $1/R_{eq}$ was set to −11 in the simulation. The typical governor actuator time constant, $T_G$, is 0.2 seconds. For stable performance of the speed control, a transient droop compensation, which is a lead-lag transfer function with time constants $T_1$ (2 seconds) and $T_2$ (12 seconds), was introduced between governor and turbine. The turbine model represents mechanical power output following the governor action and is characterized by a time constant $T_I$ (0.3 seconds). The parameters of this simplified responsive synchronous plant model, which captures the characteristics of different turbines and governors, were determined based on a severe frequency event that occurred in the GB on 27th May 2008 [15].

It is anticipated that the characteristics of the responsive synchronous plants will not change by 2020 (most of the responsive synchronous plants that will be in service in 2020 have already been built and new plants will have similar characteristics). Only their operational capacity on the system will change as some of them will be replaced by wind generation. The majority of the wind power plants and other renewable generation plants are connected to the power system through a power electronic interface. They will not respond to frequency changes thus making no contribution to $\Delta P_m$.

The operational generation capacity on the 2020 system was considered when calculating $H_{eq}$. For the 2020 system, $H_{eq}$ was calculated as 4.44 seconds, which was obtained from previous research [17].

The damping provided by the frequency dependent loads is represented by a single damping constant $D$, which was set to 1.0. $T_{EV}$ is a time constant to model the EV charger time delay.

C. Generic EV Charger Model

A generic EV charger model shown in Fig. 3 was used. It consists of a DC-DC converter to step down the voltage to an appropriate level for the EV battery charging and an inverter connected to the grid through a small reactor $L_r$ [18]. The resistor $R_{eq}$ represents the resistance of the reactor and the inverter losses. The inverter is switched using a PWM switching technique. As described in [10] active and reactive power control was employed through vector control and to generate modulating signals for PWM.
The current between the inverter and the grid is given by [19], [20]:
\[
L \frac{di}{dt} + Ri - V_{grid} + V_{EV} = 0
\]  
(1)

If the modulation index of the PWM modulation used for inverter is \(m\) and angle between \(V_{EV}\) and \(V_{grid}\) is \(\delta\), then \(V_{EV}\) is given by [19], [20]:
\[
V_{EV} = \alpha MV_{DC} \sin(\omega t + \delta)
\]  
(2)

where \(\alpha\) is a constant (0.5 or 1) depending on the exact topology of the inverter.

Equation (1) shows that the current, thus power, exchanged between the inverter and the grid is governed by a first order differential equation. Therefore for frequency studies a first order lag with a time constant \(T_{EV} = L/R\) was used (Fig. 2).

III. ELECTRIC VEHICLE LOAD ESTIMATION TOOL

The charging load drawn by an EV depends on battery type, battery capacity, maximum travel range, travel distance within a day and the time that charging starts. The EV database created by the EU “MERGE” project provides such information obtained for all EVs intended for the European market [12]. Based on the deterministic information provided in that database, appropriate probability density functions were identified and random sampling was used to estimate the EV charging loads [21].

A. EV Classifications

Individual EVs were classified based on the following two parallel EV classifications.

- **Classification based on the use of transport.** In the UK, 61% of vehicles are privately owned primarily for commuting (home based work, HBW), 9% are company owned and used primarily for business purposes (non-home based, NHB), and 30% are owned by people who do not commute, generally characterized by those retired from work or who are unemployed (home based other, HBO) [22]. Each EV considered in the EV load estimation tool was assigned to one of the above three groups (HBW, HBO, and NHB).

- **Classification based on the type of vehicles.** Based on a survey of the European EV market, four types of EVs were identified for the EV database. These are listed as [12]:

<table>
<thead>
<tr>
<th>Classification</th>
<th>L7e</th>
<th>M1</th>
<th>N1</th>
<th>N2</th>
</tr>
</thead>
<tbody>
<tr>
<td>2020</td>
<td>8,281</td>
<td>486,341</td>
<td>55,576</td>
<td>5,558</td>
</tr>
</tbody>
</table>

- **L7e:** Quadricycle-four wheels, with a maximum unladen mass of 400 kg or 550 kg for goods carrying vehicles.
- **M1:** Passenger vehicle, four wheels up to 8 seats in addition to the driver’s seat.
- **N1:** Goods-carrying vehicle, four wheels, with a maximum laden mass of 3500 kg.
- **N2:** Goods-carrying vehicle, four wheels, with a maximum laden mass between 3500 kg and 12,000 kg.

The number of EVs in different groups (L7e, M1, N1, N2) that are anticipated in 2020 is listed in Table I [12]. They constitute 1.74% of vehicles in Great Britain in 2011 (around 32 million of these four types of vehicles were licensed for use in GB at the end of 2011 [23]).

In the simulation, each EV was assigned to one of the four groups based on the statistics provided in Table I.

B. Charging Load Profile of an Individual EV

The following procedures were used to determine the charging load of an individual EV.

- **a)** The capacity of an individual EV battery, \(Cap_r\), was determined using the probability distribution of EV battery capacity derived from the MERGE EV database.

  The histogram of battery capacity of each EV type in the EV database is shown as the dotted lines in Fig. 4. A number of probability distributions were then fitted to determine the most suitable probability density function (pdf). For example, it was found that the Gamma distribution provided the best approximation for M1 type EVs. A similar process was used to obtain the pdfs of other three EV groups and the results are given in Fig. 4. The parameters of each pdf are given in Table II.

  The parameters used in each pdf in Table II are defined by (3) for the Gamma distribution and (4) for the Normal distribution.

  \[
  f(Cap_r; \alpha, \beta) = \frac{1}{\beta^\alpha \Gamma(\alpha)} Cap_r^{\alpha-1} e^{-\frac{Cap_r}{\beta}}
  \]  
  (3)

  \[
  g(Cap_r; \mu, \sigma) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(Cap_r - \mu)^2}{2\sigma^2}}
  \]  
  (4)

  For each EV, random sampling of the pdf was used to generate the battery capacity. Matlab functions “gamrnd” (for gamma distribution) and “normrnd” (for normal distribution) were used to generate a capacity based on each probability distribution. If the capacity generated was not within the maximum (Max) and minimum (Min) kWh constraints, the process was repeated until the constraints were satisfied.

  \- **b)** Based on the battery capacity \(Cap_r\) generated in step (a), the corresponding maximum travel range \(\text{Range}\) was obtained.

  The EV database provides discrete values of the maximum travel range for different EVs. Polynomial fitting was used to determine the mathematical relationship between \(\text{Range}\) and \(Cap_r\).
Fig. 4. The probability distribution of EV battery capacity. (a) L7c; (b) M1; (c) N1; (d) N2.

**TABLE II**

<table>
<thead>
<tr>
<th>EV group</th>
<th>L7c</th>
<th>M1</th>
<th>N1</th>
<th>N2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distribution</td>
<td>Gamma</td>
<td>Gamma</td>
<td>Normal</td>
<td>Normal</td>
</tr>
<tr>
<td>Parameter</td>
<td>$\alpha$=10.8, $\beta$=0.8</td>
<td>$\alpha$=4.5, $\beta$=6.3</td>
<td>$\mu$=23.0, $\sigma$=9.5</td>
<td>$\mu$=85.3, $\sigma$=28.1</td>
</tr>
<tr>
<td>Max (kWh)</td>
<td>15.0</td>
<td>72.0</td>
<td>40.0</td>
<td>120</td>
</tr>
<tr>
<td>Min (kWh)</td>
<td>5.0</td>
<td>10.0</td>
<td>9.6</td>
<td>51.2</td>
</tr>
</tbody>
</table>

Fig. 5. The relationship between EV battery capacity and maximum travel range.

Take M1 as an example, the squares in Fig. 5 show the maximum travel range of each type of M1 EV versus its battery capacity, and the stars shows the result of polynomial fitting.

c) Determine the EV daily travel range.

$D_{\text{sa}}$ is the EV’s daily travel range which was obtained through the pdf in (5) [22]:

$$h(D_{\text{sa}}; \mu, \sigma) = \frac{1}{D_{\text{sa}}\sqrt{2\pi\sigma^2}}e^{-\frac{(\ln(D_{\text{sa}}) - \mu)^2}{2\sigma^2}}, D_{\text{sa}} > 0$$

(5)

The parameters in (5) were determined by the EV classification based on the use of transport. For HBW and HBO, the mean of distribution ($\mu$) is 22.3 miles and the standard deviation ($\sigma$) is 12.2 miles. While for NHB, the mean is 54.1 miles and the standard deviation is 15.2 miles [22].

d) Determine the initial state of charge ($S_0$) when an EV starts to charge.

Assuming the state of charge (SOC) drops linearly with the travel distance [22], $S_T$ was determined by (6):

$$S_T = S_0 - D_{\text{sa}}/\text{Ran}$$

(6)

where $S_0$ is the SOC of an EV before travel and was generated using random sampling assuming $S_C$ varies uniformly in the range of $[0.8\%, 0.9\%]$ (80%-90% SOC was used in order to maintain the lifetime of a battery [12]).

e) Determine battery start charging time $t_s$

The charging time of an EV battery is determined by people’s daily transportation behaviour and the charging strategies used. Three charging strategies were considered to determine $t_s$. The method to model smart charging was from [8] while the methods to model dumb charging and off-peak charging were developed in this paper using the approach of [8].

- “Dumb” charging

All EVs were assumed to start charging just after coming back from their daily trips. The pdf of $t_s$ is given by (7):

$$f(t_s; \mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{(t_s - \mu)^2}{2\sigma^2}}$$

(7)

It was assumed that $\mu$ is 18:00 and $\sigma$ is 4 hours.

- “Off-peak” charging

Off-peak charging is used as an incentive to encourage EV users to charge during the off-peak time. The peak load time was defined as from 7:00 to 20:59 and the “off-peak” load time was defined as from 21:00 to 6:59. Since all the EVs should have been charged at the end of the “off-peak” time, $t_s$ varies uniformly from 21:00 to 23:00.

- “Smart” charging

It was envisaged that there will be an active management system based on two hierarchical control structures, one headed by an Aggregator and the other by the system operators (TSO/DSO). Further it was assumed that EV charging is controlled according to the Aggregator’s market negotiations or according to the need of the system operators. Smart charging is described by (7) with $\mu$ equals to 1:00 and $\sigma$ equals to 5 hours [8]. Compared to “Dumb” charging, the model of “Smart” charging represents the shift of EV charging load from the system peak demand time to the valley hours.

f) Obtain the vehicle charging load with the corresponding SOC profile.

In order to obtain the vehicle charging loads and corresponding SOC profiles, lead-acid and Li-ion batteries, which are expected to be the two dominant battery technologies in 2020 [12], were used in the EV load estimation tool. It was assumed that 60% of the EV batteries are Li-ion and 40% are lead acid. The battery charging load and related SOC profiles of the two types of batteries in [24] and [25] were discretized with its discrete values $P_t$ and $S_t$ taken in hourly interval and shown in Fig. 6 as the reference batteries. $\text{Cap}_{\text{ref}}$ represents capacity of the reference batteries, which is 27.19 kWh for
Fig. 6. Battery charging profiles of Li-ion and lead-acid batteries.

Fig. 7. Charging profile of a randomly selected battery (lead-acid).

lead-acid or 29.07 kWh for Li-ion when fully charged from a full discharged state [24] and [25].

The charging load of all EV batteries was assumed to follow the same shape as the reference batteries shown in Fig. 6. However, depending on the capacity of the battery, the charging time was adjusted accordingly. This was done by multiplying the x-axis (time-axis) by a coefficient $\beta$ defined by (8):

$$\beta = \frac{Cap_r}{Cap_{max}}$$

where $Cap_r$ is the capacity obtained in step (a).

For an EV battery with capacity $Cap_r$, the charging profile was obtained by considering $S_0$ and $S_f$ obtained in step (d). Using a lead-acid battery as an example, the nearest integers to $S_0$ and $S_f$ were first obtained and marked as points A and B in Fig. 7. These points were then projected to the power demand profile (marked as points C and D).

Once $t_*$ was obtained in step e) using random sampling, the power demand profile between points C and D of Fig. 7 with the corresponding SOC profile between A and B were mapped to the 24-hour coordinate to determine the vehicle charging load along a day, which is shown in Fig. 8.

C. Charging Load Profile of Multiple EVs

For $n$ EVs, the procedure defined in part B was repeated $n$ times. Each EV’s charging load with its SOC profile along a day was recorded. The total vehicle charging load ($Pn_t$) for $n$ EVs at specific time $t$ was defined as (9):

$$Pn_t = \sum_{i=1}^{n} P_i^t$$

$t = 1, 2, \ldots, 24$

Fig. 8. EV charging load from a lead-acid battery with charging starts at $t_*$.

It was assumed that when a frequency event occurs, only the EVs with $SOC \geq l\%$ will contribute to the primary frequency response, where $l\%$ is the pre-defined SOC threshold. As a result, the total vehicle charging load available for primary frequency response at specific time $t$ was obtained by (10).

$$Pn_{t, SOC_{\geq l\%}} = \sum_{i=1}^{n} P_i^t \cdot \eta_i$$

$\eta_i$ is defined in (11):

$$\eta_i = \begin{cases} 1, & S_i^t \geq l\% \\ 0, & S_i^t < l\% \end{cases}$$

IV. EVS FOR FREQUENCY RESPONSE

The GB power system model shown in Fig. 2 was used to investigate the contribution of EVs to the primary frequency response.

A. Case Study

An EV can participate in low frequency response services in two ways. One approach would be to switch off EVs that are being charged. In the other approach, EVs could support the grid by acting as a power source. In this case, it is assumed that the EV battery charging and the state of charge profiles (Fig. 7) are reversible [26]. The power sent back to the grid by an EV is assumed constant during the time it is providing the primary frequency response, and is equal to the power absorbed by the same EV before the response. The following two cases were investigated:

• Case I: Vehicles charging with a state of charge equal to or greater than a pre-defined threshold $\{SOC \geq l\%\}$ were disconnected from the grid.
• Case II: Vehicles charging with a state of charge equal to or greater than a pre-defined threshold $\{SOC \geq l\%\}$ were discharged to the grid.

B. Simulation Results

The vehicle charging load with four state of charge thresholds ($l\% = 0\%, 40\%, 60\%, 80\%$) were obtained by the EV load estimation tool using the procedures described in Section III for
Fig. 9 shows the frequency profiles under different EV charging mode when 1800 MW of generation was disconnected from the GB system at 21:00. Fig. 11 shows the minimum frequency when system suffers a loss of 1800 MW generation at every 30 minutes under different EV charging strategies with two control modes. The results show that the effectiveness of using EVs for primary frequency response has a close relationship with the EV’s charging strategies and different state of charge thresholds \( [%] \). At 21:00, “off-peak” charging showed the best primary frequency response capability than the other two charging strategies. Primary frequency response capability of Case II is better than that of Case I. As depicted in Fig. 10(f), when all EVs with SOC \( \geq 40\% \) or SOC \( \geq 60\% \) responded to the frequency event under Case II, the frequency was higher than 50.1 Hz during the subsequent transient, which means that not all the EVs being charged needed to respond to the frequency event. The amount of vehicle charging load for primary frequency response should be decided by the frequency drop. The state of charge threshold \( [%] \) is an important indicator for selecting EVs to respond the frequency events.

C. Results Comparisons

In order to evaluate the impact of EV battery charging strategies on primary frequency response, the lowest frequency throughout 24-hour under Case I and Case II with SOC \( \geq 80\% \) was given in Figs. 12 and 13. Results show that the primary frequency response capability under different charging strategies has obvious temporal distribution along a day. Therefore requirements to schedule frequency response from conventional generators are dynamic throughout the day.

D. Impact From EV Charger

The results didn’t consider the response delay caused by the EV charger. In this section, the generic EV charger was used to model the induced response delay. For case I, EV chargers have negligible impact on the primary frequency response due to the simple “trip off” operation. Therefore results are only presented for the Case II study.

\( L \) was taken to be equal to 7 mH and \( R \) equal to 0.2 Ohms [28] for the generic EV charger model shown in Fig. 3 \( (T_{EV} = 35 \text{ ms}) \). Another two sets of \( L \) and \( R \) parameters obtained from different EV charger manufacturers were also used for comparison \( (T_{EV} = 50 \text{ ms} \) and 100 ms respectively). Results shown in Fig. 14 showed that the time delay caused by EV chargers is negligible.

V. CONCLUSION

The potential of using EVs for primary frequency response in the GB power system at the year of 2020 was investigated. An EV load estimation tool was developed to obtain the 24-hour vehicle charging load. The tool was integrated to a simplified GB system for the primary frequency response study. It was assumed that the characteristics of frequency responsive synchronous plants will not change in 2020 and only their operational capacity on the system will change as some of them will be replaced by wind generation. The inertia of the 2020 GB system was chosen to reflect a high penetration of renewable sources.
The EV charging load profiles under three charging strategies with two control modes were considered. During a low frequency event, the EV charging load with different state of charge thresholds was used for primary frequency response. The following conclusions can be drawn:
• EVs have great potential to provide effective system primary frequency response. However, the contribution from EVs has an obvious temporal distribution along a day. Therefore requirements to schedule frequency response from conventional generators are dynamic throughout the day.

• The ability of EVs to provide primary frequency response has a close relationship with EV charging strategies. EVs with “dumb” charging and “off-peak” charging are able to provide significant contribution to the primary frequency response at specific time periods when the EV charging load is heavy. On the contrary, “smart” charging can distribute this capability to most times throughout the day.

• There is negligible impact of the time delay induced by EV chargers on the provision of primary frequency response from EVs.

The simulation results show that sometimes not all EVs being connected to the grid need to provide primary frequency response, thus an important topic for future research is how to determine an optimal amount of EVs to participate in the primary frequency response.

REFERENCES


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