Vehicle-to-Grid Aggregator to support power grid and reduce Electric Vehicle charging cost

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ABSTRACT This paper presents an optimised bidirectional Vehicle-to-Grid (V2G) operation, based on a fleet of Electric Vehicles (EVs) connected to a distributed power system, through a network of charging stations. The system is able to perform day-ahead scheduling of EV charging/discharging to reduce EV ownership charging cost through participating in frequency and voltage regulation services. The proposed system is able to respond to real-time EV usage data and identify the required changes that must be made to the day-ahead energy prediction, further optimising the use of EVs to support both voltage and frequency regulation. An optimisation strategy is established for V2G scheduling, addressing the initial battery State Of Charge (SOC), EV plug-in time, regulation prices, desired EV departure time, battery degradation cost and vehicle charging requirements. The effectiveness of the proposed system is demonstrated using a standardized IEEE 33-node distribution network integrating five EV charging stations. Two case studies have been undertaken to verify the contribution of this advanced energy supervision approach. Comprehensive simulation results clearly show an opportunity to provide frequency and voltage support while concurrently reducing EV charging costs, through the integration of V2G technology, especially during on-peak periods when the need for active and reactive power is high.

INDEX TERMS Electric vehicle, vehicle-to-grid, battery degradation performance, frequency regulation service, voltage regulation service, charging cost, day-ahead scheduling, smart-grid.

NOMENCLATURE

Sets and Indices

i	Charging station index
j	Electrical vehicle index
BT_{ij}	Battery chemistry type of the E_{ij}

Symbols and Acronyms

EV	Electric Vehicle,
CS	Charging station,
TSO	Transmission system operator,
D-Day	V2G operation day,
DSO	Distribution system operator,
min	Minimum,
$s.t.$	Subject to,
SOC, s	State of charge,
DOD, D	Depth of discharge,
AWC	Average wear cost,
WDF	wear density function,
W	WDF at the state-of-charge s,
Sol	Available set of solutions for optimisation problem,
V2G	Vehicle to Grid power flow operation,
G2V	Grid to Vehicle power flow operation,

Functions and Variables

SOC_{ij}^{ini}	The initial SOC of the E_{ij},
SOC_{ij}^{fin}	The final SOC of the E_{ij},
$SOC_{ij}(t)$	The actual SOC of the E_{ij},
E_{ij}^{ini}	The initial energy of the E_{ij},
E_{ij}^{fin}	The final energy of the E_{ij},
E_{ij}^{max}	The maximum energy of the E_{ij},
$P_{ij}^{\uparrow}(t)$	The regulation up signal of the E_{ij},
$P_{ij}^{\downarrow}(t)$	The regulation down signal of the E_{ij},
$P_{ij\_new}^{\uparrow}$	The updated regulation up signal of the E_{ij},
$P_{ij\_new}^{\downarrow}$	The updated regulation down signal of the E_{ij},
$Q_{ij}(t)$	The reactive power of the E_{ij},
$Q_{ij_{new}}$	The actualized reactive power of the E_{ij},
T_{ij}^{ini}	The arrival time of the E_{ij},
T_{ij}^{fin}	The departure time of the E_{ij},
T_{ij}	V2G operation period of the E_{ij},
N_{Cycle}	Cycle life,
$£^{B}, £_{ij}^{B}$	Total Wear Cost of battery of the E_{ij},
$J_{,1,2}(x)$	Objective functions,
x	Optimal solution set,
t	Time,
$V_i(t)$	Voltage to neutral at the connection point of the CS i,
$\Delta V_i(t)$	Voltage fluctuation at the connection point of the CS i,
$R^{ref}(t)$	Active power signal from TSO,
$Q^{ref}(t)$	Reactive power signal from DSO,
$P^{\uparrow}(t)$	Regulation up capacity of the aggregator,

$P^{\downarrow}(t)$	Regulation down capacity of the aggregator,
$Q(t)$	Reactive energy regulation capacity of aggregator,

Parameters and constants

T_{step}	Interval Set,
n	Number of interval Set,
S_{ii}	Rated power of the charger supplying the E_{ij},
q_{ij}	Allowable reactive power generation of the E_{ij} charger,
q^{max}, Q_{ij}^{max}	Maximum reactive power generation of the E_{ij} charger,
Q_i^{max}	Maximum reactive power generation of CS i,
p_{ij}	Instantaneous real power drawn from the grid by E_{ij},
α, β	Battery specific coefficients,
$\mathbb{P}, \mathbb{P}_{ij}$	Battery price of the E_{ij},
η	Cycle efficiency,
$\eta_{ii}^{\downarrow}, \eta_{ii}^{\uparrow}$	Regulation down/up charger efficiencies,
$\pounds_R^{\downarrow}, \pounds_R^{\uparrow}$	Energy price/reward for regulation down/up,
P_{ii}^{max}	Maximum active power of charger supplying the E_{ij},
$\pounds_Q(t)$	Reactive energy reward for voltage regulation service,
g_i, x_i	Line conductance / reactance upstream of the CS node,
N_{EV}	Total number of EVs within aggregator,
$N_{charger}$	Total number of EV chargers within aggregator.

I. INTRODUCTION

ELECTRIC VEHICLES (EVs) play a vital role in dealing with the fossil-fuel energy crises and reducing carbon emissions. To effectively use the full potential of EVs as a flexible grid-connected energy resource, EVs can be controlled to not only charge, but also return energy back to the grid at optimal times. Such a capability within an EV – charger system is called Vehicle to Grid (V2G) and is done using a built-in bidirectional DC-AC converter [1]. This technology underpins the ability to transform the vehicle into a Distributed Energy Resource (DER) with the potential for smart grid integration [2-3]. The successful deployment of V2G has shown great promise in areas of voltage regulation [4], spinning reserve [5], load peak shifting [6] and frequency regulation [7]. In particular, grid frequency regulation has received significant attention from the academic community [6-7]. Frequency of the electrical supply is one of the most important stability indexes often employed with power system operation and must be controlled within limits defined by the regulating authorities. Because of the real-time response characteristics of EV chargers (typically in the order of 10 ms), EVs participating in up/down regulation have a natural advantage over other regulation entity services, such as a synchronous machine. EVs can also be considered as a form of regulating resource, such as participating in further supplementary frequency regulation [8]. For a distributed power grid, the on-site generation of reactive power has an important additional value, as discussed in [9]. Therefore, generating V2G reactive power will further help the energy utility by providing increased efficiency of power transfer through transmission lines and by reducing the possibility of transformer overload conditions occurring, while it is

proposed that the EV battery performance is not degraded by reactive operation [9-10].

This paper presents a novel control system to underpin bidirectional V2G operation using a fleet of EVs, allowing the V2G aggregator to provide frequency and voltage regulation services to the power grid, minimizing the charging cost, maximizing the V2G operational benefit and minimizing the level of battery degradation. This energy supervision is able to fulfill the following objectives:

1- Perform day-ahead scheduling of V2G operation for each EV, to estimate the D-day frequency and voltage regulation capacity for grid support, while satisfying EVs owner and grid constraints,

2- Reducing the charging cost for EV owner without increasing battery degradation, by giving frequency support, and increasing the daily aggregator benefit using grid voltage support.

3- Identify the intraday schedule changes that are required or economically interesting to undertake under various contingencies into account.

The nonlinear programming (NLP) model of the deterministic problem is presented with the objective of simultaneously minimizing the degradation cost of EVs batteries and maximizing the benefit of EV owner while participating in V2G operation (i.e. frequency and voltage regulations). This objective is subject to system operation constraints and limitations associated with EVs operation. A mathematical framework is presented to address frequency deviations at grid level using a fleet of EVs, providing bi-directional V2G support and minimizing battery degradation. The proposed scheme is then verified using IEEE 33 bus grid system as a representative case study, results shown within this study, confirm the ability of the proposed scheme, to give support to the distribution power grid while, reducing the charging cost, maximizing the operational benefit and minimizing the level of battery degradation.

The remainder of this paper is organized as follows. In Section 2, the V2G based aggregator architecture is introduced and in Section 3, a V2G Scheduling Optimisation is proposed for EVs. The required hierarchical supervisory and control functions are described in Section 4. Case Studies are presented and discussed in Section 5. Finally, Section 6 draws the primary conclusions and recommendations for further work.

II. VEHICLE TO GRID-BASED ON AGGREGATOR TECHNOLOGY

A. Aggregator Strategy

Different strategies for V2G aggregation are being proposed by researchers within both the academic community and industry [11]. The aim of each aggregation strategy often depends on the objective of the control system. Optimal aggregation strategies are proposed to reduce the cost functions related to energy cost for a pre-defined set of

grid utilities or even the charging price for EVs owners. These strategies often also consider different ancillary service markets such as regulation, peak power and cost minimization.
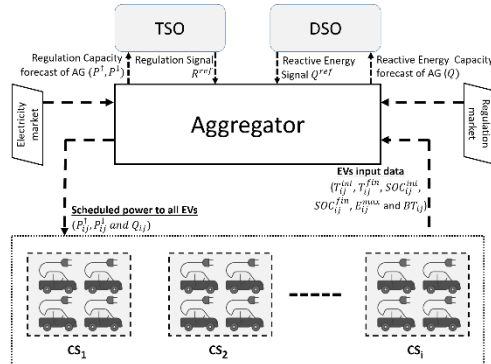

FIGURE 1. Aggregator scheme as an interface between EV fleet and grid operator

One example structure of the proposed aggregator for frequency and voltage services is depicted in Figure.1 [12]. This form for of architecture was selected for this research because its high level of flexibility and simplicity to manage it. Figure.1 shows the flow of necessary information between EV fleets, the aggregator and the power system operator for system optimisation to be viable. The aggregator, based on the received information makes a decision to a set of EVs charging/discharging command. These decisions are based on the regulation market price (e.g. £/kWh) and regulation reference announced by the grid operator (Transmission System Operator "TSO" and Distribution System Operator "DSO"). In this model, there is only one aggregation entity managing the EVs through different charging stations. This assumption is consistent with research published within [12]. Regulation signals mainly comprise of two types; "regulation up" when the production of energy is less than consumption and "regulation down" when the production of energy is more than consumption from the grid. During a period of vehicle connection, the EVs can undertake different actions in order to respond to the different regulation signals (Figure 2.).
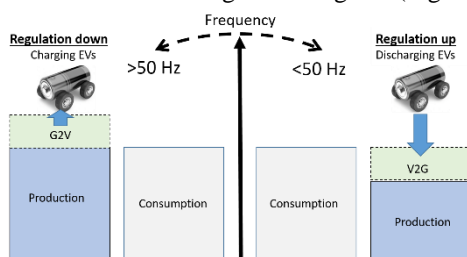

FIGURE 2. Aggregator decision based on regulation signal

As reported by [1]-[14], the EV owner is able to collect revenues or incur costs when they are connected to a V2G charger. The aggregator distributes the revenue that is delivered to the aggregator from the TSO/DSO to vehicle owners that have been connected to that aggregator's V2G charger network during V2G operation. For providing regulation services, the aggregator coordinates registered EVs and can communicate with each EV bi-directionally when the EV is plugged-in. The assumption is made that each EV provides regulation services only when connected.

B. Vehicle-to-Grid Architecture

V2G is primarily composed of bidirectional charging stations and EVs along with communication and charging facilities. A simplified system architecture is illustrated in Figure.3. Charging stations (CS) are deployed to monitor each EVs/V2G charger and group them together such that when aggregated they have sufficient energy capacity to have a meaningful impact on the grid. Usually, as discussed within [1] at least a few hundred of EVs should be aggregated to provide/absorb MWh-level electrical energy to/from the power grid. Examples of systems reported in the literature include 500, 1000 and 1500 EVs. To place this further into context, 1MWh of energy storage would be provided by circa 25 Nissan Leaf cars of each 40kWh battery capacity each. To this end, for each EV parking space, a charging device may be deployed, through which the parked EV can connect to the smart grid to trade electricity.
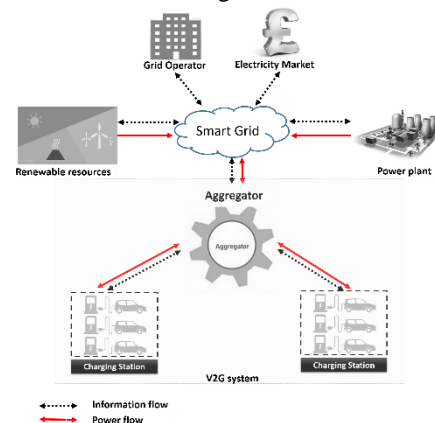

FIGURE 3. Vehicle-to-Grid System Architecture

Charging stations are directly connected to the aggregator as hierarchical structures (Figure 3.). The energy aggregator is responsible for overall system monitoring and co-ordinates transactions on behalf of the EVs based on the varying market price and/or grid operator energy requests. Each CS is responsible for directly monitoring EVs parked within its local area and reports the collected data (e.g., EV SOC, Arriving time, Departure time, final SOC etc…) to the aggregator, typically in a batch mode of data communication, which is known to be an efficient way to monitor a large volumes of EVs [13] (Figure 4.).
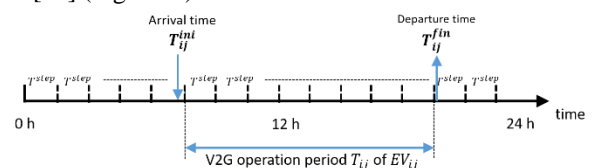

FIGURE 4. V2G operation time range

In Figure.3, there are primarily two flows through the smart grid; the information flow and the electricity flow. The information flow typically comprises key technical information including battery SOC, economic data like electricity price and statistical information like power availability [13]. The smart grid operator sends demands to the aggregator, which in turn requests the EVs to provide the demanded services, e.g., discharging the EV to route the previously stored energy from the EVs to the grid. Although individual EV's plug availability is unpredictable, the availability of hundreds of EVs can be estimated from traffic or road-use data, as described in [14]. As a further example, in the US the average car is driven only one hour a day [15]; over 92% of vehicles are parked and therefore potentially available to the grid during even within the peak traffic hours [16].

III. FORMULATION OF THE V2G SCHEDULE OPTIMISATION PROBLEM

Within a practical system, V2G optimisation is performed by the aggregator, as it will provide the data interface between the EVs and the grid operators. V2G scheduling optimisation is typically based on a regulation up and regulation down price (£/kWh). To further refine the optimisation approach, an EV battery wear cost model and power grid state is formulated within this section. The solution to the optimisation problem provides an optimal scheduling scheme which minimizes the total cost of EV operation and maximizes the total benefit of EVs ownership participating in frequency and voltage grid support.

A. System Modeling

V2G operation using EVs batteries will be studied during a typical day, which is evenly divided into a set of time intervals. The interval set is denoted by T_{Step}. In this paper, we divide the day into n intervals such that the length of an interval is given by $24/n$. We assume that the charging or discharging power within interval is kept unchanged (Fig.4) during each interval. The regulation up / down signal of jth EV$_{ij}$, located on the ith charging station within interval t is denoted by $P_{ij}^{\uparrow}(t)$ and $P_{ij}^{\downarrow}(t)$ respectively. The arrival time of jth EV$_{ij}$, denoted by T_{ij}^{ini}, is the time when the jth EV$_{ij}$ is plugged into the ith charging station. The departure time of jth EV$_{ij}$, denoted by T_{ij}^{fin}, is the time when the jth EV$_{ij}$ is unplugged from the ith charging station.

The total V2G operation period of the jth EV$_{ij}$, located on the ith charging station, denoted by T_{ij}, is the period in which EV$_{ij}$ charges and/or discharges its battery at the parking period time. Since we divide the time into multiple intervals, we define the charging period T_{ij} of EV$_{ij}$ as the set of continuous intervals that fall between the arrival time T_{ij}^{ini} and the departure time T_{ij}^{fin}, as illustrated in Fig.4. The initial energy of EV$_{ij}$, denoted by E_{ij}^{ini}, is defined as the battery energy at the arrival time T_{ij}^{ini} while the battery capacity is denoted by E_{ij}^{max}. For practical applications for the vehicles, a final

energy E_{ij}^{fin} is defined as the energy within the battery at the departure time T_{ij}^{fin}, its value should be high enough, to allow the outgoing vehicle, to meet the next travel plan. The final energy E_{ij}^{fin} is no larger than the battery capacity E_{ij}^{max}. The charging station can automatically detect the arrival time, the initial energy and the battery capacity of EV$_{ij}$ when the EV is plugged-in. The departure time, and the final energy requirement of EV$_{ij}$, are provided to the charging station by the EV owner, before the charging operation is started. The charging station can determine the charging/discharging operation period T_{ij} of EV$_{ij}$. The regulation up/down price and voltage regulation price at a time instant is the same regardless of the charger location. The optimisation of the EV charging based on only temporal variation but not spatial variation of the price has been seen in [2].

B. Frequency regulation

A potential benefit of the integration of EVs is the ability to maintain the reliable operation of the grid through coordination between the vehicle and the utility. V2G technology enables EVs to provide frequency support service for the power grid system. The EVs are contracted with the TSO through aggregator, and TSO provides economic incentives for EVs participating in the regulation up/down service. When an EV provides the regulation service, the net energy exchange tends to be zero over a prolonged time [17]. Thus, the EVs are paid by their power capability that they provide for frequency regulation. This value can be in the order of some few of kW, according to the capacity of EV battery [12]. Table II, summarises the battery characteristics of exiting commercially available EVs. From the Table II, BYD e6, Nissan e-NV and Nissan Leaf vehicles are particularly noteworthy since they are able to engage in V2G operation.

C. Voltage regulation

Voltage regulation studies show that the DC link capacitor of the EV charger is sized, in terms of Farads, to supply reactive power to the grid even without engaging the EV battery. Thus, it is proposed that voltage regulation causes no degradation within EVs battery [18]. The amount of reactive power for voltage regulation that the charger can supply during charging mode is limited by the charger's power limit and the amount of active power drawn from the grid. Thus, until the off-board charging station fully charges the battery, the reactive power support capacity of the EV is defined as [19]:

$$q_{ij} \leq \sqrt{S_{ij}^2 - p_{ij}^2} = q_{ij}^{max} \qquad (1)$$

If the battery is drawing maximum power from the charger, then the charger is not capable of producing reactive power. However, if the apparent power capability of a charger exceeds the instantaneous real power (p_{ij}) drawn from the grid by the battery, the range of allowable reactive power generation is given by the (1).
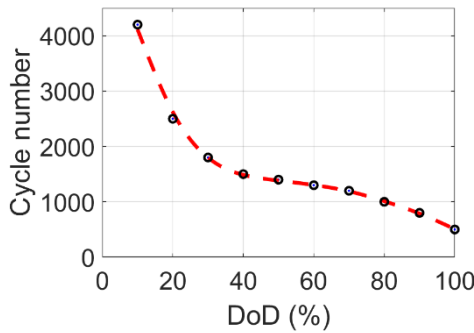
D. Battery degradation cost modelling

FIGURE 5. Lithium-Ion DOD cycle life model [20]

A typical lithium-ion battery has a similar Depth Of Discharge (DoD), Cycler number characteristic to that shown in Figure.5 which are derived from empirical datasheet of lithium-ion battery, which fits with the following function (2) [20]:

$$N_{Cycle}(D) = \frac{\alpha}{D^\beta} \qquad (2)$$

Where D denotes depth of discharge of the battery and N_{Cycle} is the cycle life. Within this model, degradation effects due to ambient temperature are omitted. Both α and β are battery specific coefficients, and can be obtained experimentally via an ageing study, for example similar to that discussed within [20]. In [20] the authors propose the average wear cost (AWC) per unit energy transfer as:

$$AWC(D) = \frac{\text{Battery Price (£.kWh)}}{\text{Total Transferable Energy During the Life Cycle (kWh)}}$$
$$= \frac{\mathbb{P}}{N_{Cycle}(D) \times 2 \times D \times E^{max} \times \eta^2} \qquad (3)$$

where $\mathbb{P}$ is the battery price, E^{max} is the battery capacity, and η is the cycle efficiency. The cycle account N_{Cycle} is multiplied by two as one cycle consists of charge and discharge phase, for which, the same amount of energy is transferred. Note that this AWC represents the unit wear cost for cycling a battery within a specific SOC range. However, in V2G applications, [20] propose a more general index called wear density function (WDF) that provides wear information for any given SOC point (4):

$$AWC(D) = \frac{1}{D} \int_{1-D}^{1} W(s) ds \qquad (4)$$

Where $W(s)$ is the WDF at the state-of-charge s. Since AWC indicates the average wear cost at the given D, it can be represented by integrating $W(s)$ within the corresponding SOC range and dividing it by the length of the integration window. Since the AWC is valid only for the specific SOC range, if the battery is cycled at a different SOC, which is the case for a V2G application, the wear cost would yield a different value. However, the total wear cost can be calculated for any kind of profile using the generalised following equation [20]:

$$£^B = E^{max} \times \int_0^T W(s(t)) \times \left| \frac{ds(t)}{dt} \right| dt \qquad (5)$$

where $£^B$ is the Total Wear Cost and T is the horizon size.

E. Problem formulation

In this section, the deterministic NLP formulation of the V2G management problem is presented. Further information on derivation and use of NLP is discussed within [29] and will therefore not be repeated here. The model minimizes the battery degradation cost and the difference between the energy cost and the revenue of EV's as shown in (5). Hence, the optimisation problem model is formulated as:

$$\min_x \{J(x)\}$$
$$\text{s. t. } x \in Sol. \qquad (6)$$

The mentioned optimisation can be viewed as a complex problem having two objectives such as EV battery degradation cost minimization $J_1(x)$ and EV's revenue maximization during participating within regulation service $J_2(x)$. Wherein $J(x)=J_1(x) - J_2(x)$ is the vector-valued multi-objective function under consideration. Variable x denotes the optimal solution, which belongs to the available set of solutions (*Sol*). The constraints taken into consideration impose restrictions on EV battery charging and discharging to reduce battery degradation and to maintain safe operation of the battery. The proposed work considers equal weights for all the objective functions, since these weights depict the relative importance of an objective function over another in the given context. The concept has been adopted in order to compute the optimal solution without prioritizing any function over the other [21][22][23] and [25]. In order to find a global optimal scheduling scheme for the EVs that perform V2G operation during the parking time, we assume that, the arrival time T_{ij}^{ini}, the departure time T_{ij}^{fin}, the initial energy SOC_{ij}^{ini} and the final energy SOC_{ij}^{fin} for each EV are known. Similar assumptions have been deployed in comparable studies reported in the literature [2]-[11].

1) OBJECTIVE FUNCTION FORMULATION

The global scheduling optimisation problem using the objective function $J(x)$ can be stated s to minimize EV battery degradation cost and maximize EV's revenue from V2G operations for regulation service during vehicle parking periods. This is achieved in accordance with the following two objective problems:

$$J_1 = \sum_{i=1}^{N_{cs}} \sum_{j=1}^{N_{EV}} T_{Step}(\left|P_{ij}^\downarrow(t)\right| \times \eta_{ij}^\downarrow + P_{ij}^\uparrow(t)/\eta_{ij}^\uparrow) \times £_{ij}^B(t) \qquad (7)$$

$$J_2 = \sum_{i=1}^{N_{cs}} \sum_{j=1}^{N_{EV}} T_{Step}(\left|P_{ij}^\downarrow(t)\right| \times £_R^\downarrow(t) + P_{ij}^\uparrow(t) \times £_R^\uparrow(t)) \qquad (8)$$

$$\min_{P_{ij}^\downarrow(t), P_{ij}^\uparrow(t)} J = \min_{P_{ij}^\downarrow(t), P_{ij}^\uparrow(t)} (J_1 - J_2) \qquad (9)$$

$$-P_{ij}^{max} \leq P_{ij}^\downarrow(t) \leq 0 \qquad (10)$$

Constraints (10) specify the lower and upper bounds of the charging power.

$$0 \leq P_{ij}^\uparrow(t) \leq P_{ij}^{max} \qquad (11)$$

Constraints (11) specify the lower and the upper bounds of the discharging power.

$$0.05 \leq SOC_{ij}(t) + \left(\frac{P_{ij}^{\downarrow}(t) \times \eta_{ij}^{\downarrow} - \frac{P_{ij}^{\uparrow}(t)}{\eta_{ij}^{\uparrow}}}{E_{ij}^{max}}\right) \times T_{step} \leq 0.95 \quad (12)$$

Constraints defined in (12) are the instant energy constraints, which require the energy of EV_{ij} at the end of step time $t+T_{step}$ to be between SOC 5% and 95%, to optimize battery life.

$$SOC_{ij}^{ini} + \sum_{T_{ij}^{ini}}^{T_{ij}^{fin}}\left(\frac{P_{ij}^{\downarrow}(t) \times \eta^{\downarrow} - P_{ij}^{\uparrow}(t)/\eta^{\uparrow}}{E_{ij}^{max}}\right) \times T_{step} = SOC_{ij}^{fin} \quad (13)$$

Constraints (13) are the final energy constraints, all EVs should met the final energy requirement (i.e., SOC_{ij}^{fin} of EV_{ij}) at the end of V2G operation, to allow the outgoing vehicle EV_{ij}, to have enough energy for the next travel plan.

The battery degradation cost model is depicted in (14).

$$£_{ij}^{B}(t + T_{Step}) = \emptyset_{ij} \times \left[\frac{\beta \times \left\{[1 - SOC_{ij}(t + T_{Step})]^{\beta-1} - [1 - SOC_{ij}(t)]^{\beta-1}\right\}}{\alpha}\right] \quad (14)$$

Where: $\emptyset_{ij} = \frac{P_{ij}}{2 \times E_{ij}^{max} \times \eta_{ij}^2}$.

The problem formulated above represents a form of constrained nonlinear multivariable programmed problem, wherein $P_{ij}^{\uparrow}$ and $P_{ij}^{\downarrow}$ are the decision variables. These variables denote the scheduled charging and discharging rates of the EV under consideration.

2) REACTIVE POWER EXCHANGE CONSTRAINT AND BENEFIT

Another important contribution of this work is to define the benefit from grid voltage support associated with EV integration. The power electronic inverters that connect EVs to the electrical grid are assumed to be three-phase inverters with a reactive power capability. The benefit from the voltage regulation of electric vehicle E_{ij} is obtained from (15):

$$benefit = \sum_{T_{ij}^{ini}}^{T_{ij}^{fin}} T_{Step}[Q_{ij}(t) \times £_Q(t)] \quad (15)$$

Active and reactive power exchanged with the grid must always be within the power rating of the charging socket and is given by S_{ij} (16).

$$(P_{ij}^{\uparrow}(t) + P_{ij}^{\downarrow}(t))^2 + (Q_{ij}(t))^2 \leq S_{ij}^2 \quad (16)$$

Chargers can provide reactive support to power the grid, the upper limit for reactive power Q_{ij}^{max} which charger ij^{th} could provide can be mathematically modeled as (17),

$$0 \leq Q_{ij}(t) \leq Q_{ij}^{max} \quad (17)$$

Where: $Q_{ij}^{max} = \sqrt{S_{ij}^2 - (P_{ij}^{\uparrow}(t) + P_{ij}^{\downarrow}(t))^2}$

The upper limit for reactive power injection into the distribution grid node connection of the charging station i, Q_i^{max} can be mathematically modeled as (18):

$$Q_i^{max} = \sum_j \sqrt{S_{ij}^2 - (P_{ij}^{\uparrow}(t) + P_{ij}^{\downarrow}(t))^2} \quad (18)$$

The voltage limits are modeled as (19), where $\Delta V_i(t)$ is the voltage fluctuation at the connection point of charging station i to the distribution grid. This value is obtained from the active and reactive power set points for the EVs ($P_{ij}^{\uparrow}$, $P_{ij}^{\downarrow}$ and Q_{ij}):

$$\Delta V_i(t) = \frac{1}{3 \times V_i(t)}\left[\frac{1}{g_i}\sum_{j=1}^{N_{EV}}\left(P_{ij}^{\uparrow}(t) + P_{ij}^{\downarrow}(t)\right) + \frac{1}{x_i}\sum_{j=1}^{N_{EV}} Q_{ij}(t)\right] \quad (19)$$

Where g_i and x_i are line conductance and reactance upstream of the charging station node, and V_i is the phase to neutral voltage at the connection point of the charging station.

IV. HIERARCHICAL SUPERVISION AND CONTROL

A supervisory control system is defined to enable EVs participating within V2G operation from day-ahead scheduling to real-time monitoring and control. Particularly, the supervision scheme is designed for enabling EVs to participate in frequency and voltage support services. The proposed supervision is designed with a two-layer, day-ahead scheduler and hour-ahead control layers (Figure.6).
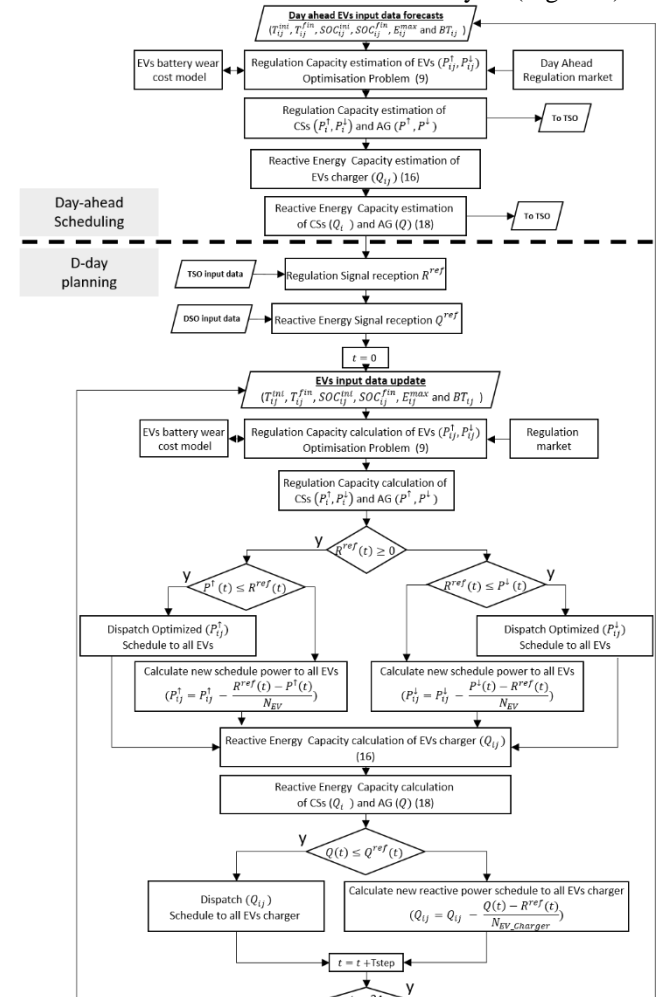

FIGURE 6. Hierarchical architecture operation

A. Day-ahead scheduling layer

The day-ahead scheduling layer is the first step for preparing day-ahead operational planning of the aggregator for the total number of EVs for the next 24 hour period. As discussed within [27], individual EV$_{ij}$ data (e.g., T_{ij}^{ini}, T_{ij}^{fin}, SOC_{ij}^{ini} etc.) are often unavailable in a day-ahead time frame. The V2G operations planning are therefore designed for aggregated EVs by considering statistical information sets [11]. Forecasted day-ahead regulation price, EV availability, statistical data and EVs battery wear cost models are used to generate the optimum EVs schedules, for the next day, and to send the frequency and voltage regulation capacity planning for the next day to the TSO and DSO respectively. The following algorithm has been implemented within Matlab software to compute the aggregated EV charging/discharging power at each step time T_{step}, using forecasted regulation price for the next day, statistical data set for EV availability at different time slots. Day-ahead scheduling, reduce the charging cost and minimize the degradation cost of EVs batteries based on the output of objective function (9), (Figure.6).

B. D-day planning layer

The D-day planning layer works within T$_{Step}$ time resolution to optimally allocate the EVs aggregated power received from day-ahead layer among the plugged-in EVs. At the beginning of the day, the aggregator receives the regulation $R^{ref}(t)$ and reactive power $Q^{ref}(t)$ signals from the TSO and DSO respectively. A conceptual framework for an hour-ahead operation is presented in Figure.6 and is described as follow:

▪ All EVs send their data (e.g., T_{ij}^{ini}, T_{ij}^{fin}, SOC_{ij}^{ini} etc...) to the aggregator through charging stations after EVs are plugged-in, those data are updated periodically within T$_{step}$ time.

▪ TSO and DSO send their active and reactive power signal. ($R^{ref}(t)$ and $Q^{ref}(t)$ respectively)

▪ The aggregator receives the actual day regulation price from the regulation market.

▪ Upon receipt of these data sets from all connected EVs and regulation market. The aggregator performs optimisation (based on equation 9) using EVs battery wear cost models, and, considering individual EV requirements to compute the new optimum operational schedules of each EV ($P_{ij}^{\uparrow}(t)$ and $P_{ij}^{\downarrow}(t)$). The new regulation capacity of the aggregator is then deducted ($P^{\uparrow}(t)$ and $P^{\downarrow}(t)$). If the new regulation capacity of aggregator is lower than or equal than the regulation signal $R^{ref}(t)$ received from TSO. The schedules are dispatched to each EV, and if the regulation capacity of aggregator is greater than the regulation signal received from TSO, the new schedules are then calculated using (19) and (20), and

dispatched to each EV.

$$P_{ij\_new}^{\uparrow} = P_{ij}^{\uparrow} - \frac{R^{ref}(t) - P^{\uparrow}(t)}{N_{EV}} \text{ if } R^{ref}(t) > 0 \quad (20)$$

$$P_{ij\_new}^{\downarrow} = P_{ij}^{\downarrow} - \frac{R^{ref}(t) - P^{\downarrow}(t)}{N_{EV}} \text{ if } R^{ref}(t) < 0 \quad (21)$$

The next computational step in the framework is to calculate the reactive energy capacity of each EVs charger Q_{ij} using (17). The new reactive energy regulation capacity of aggregator is then deducted $Q(t)$. If the new reactive energy capacity of aggregator is lower or equal, the reactive signal $Q^{ref}(t)$ received from DSO, the schedule then dispatched to each EV charger. If the reactive energy capacity of the aggregator is greater than the reactive energy signal $Q^{ref}(t)$ received from DSO, the new schedules are then calculated using (22) and dispatched to each EV charger.

$$Q_{ij_{new}}(t) = Q_{ij}(t) - \frac{Q(t) - Q^{ref}(t)}{N_{charger}} \quad (22)$$

Periodic updates on EVs schedules is then performed for each T$_{Step}$ time.

V. SIMULATION RESULTS AND DISCUSSION

To validate the proposed supervision model, two case studies have been undertaken:

• Case Study 1: The EVs participate in frequency support only. In this case, two simulation-studies are carried-out. Within the first, the scheduling process is optimised without taking account of possible battery degradation. For the second, a representative battery degradation model is included within the optimisation cost function.

• Case Study 2: The EVs participate in both frequency and voltage support. For the simulation strategy consideration is given to the evaluation of the proposed scheme is presented in detail in this section based on the real-time data acquired from [26]. The single line diagram of the 33-bus, 4-lateral radial distribution system is shown in Figure 7.
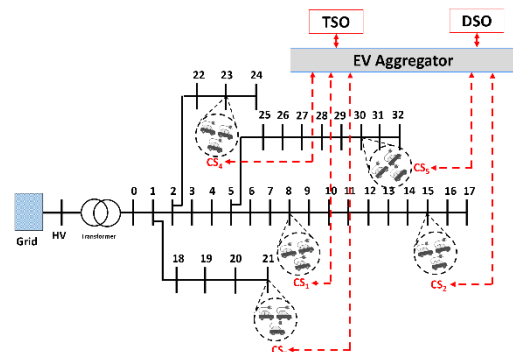

FIGURE 7. Single line diagram of 33-bus distribution system

The data from the system are obtained from [25]. In order to study the proposed V2G supervision strategy implemented in the distribution system, different locations are selected for

connection of the CSs. For this purpose, nodes 8, 15, 21, 23 and 30 of the distribution system are selected. EV departure time, arrival time and initial SOC are modelled using truncated Gaussian distribution functions [1], the final desired SOC was set at 80% for this study, to allow all outgoing vehicles, to have enough energy for the next trip. Simulation is executed for 24 hours with 30-minute time intervals. The analysed scenario includes 1000 EVs in five groups for all charging stations. The considered simulation setup takes into account the parameters illustrated in Table I for evaluating the proposed scheme on 24 hours' timescale.

TABLE I
SIMULATION PARAMETERS

Parameters	Values
No. of AGs	1
No. of CSs	5
No. of EVs/CS	200
No. of EVs	1000
Charger efficiency	90% - 95%
Charger rating	7, 22 and 50 kW
Aggregator rating	3.000 kVA

Three different electric vehicles parameters are used in the simulation model, Nissan Leaf, Jaguar I-Pace, and Tesla Model X, which their battery parameters are shown in Table II.

TABLE II
EV BATTERIES PARAMETERS [28]

EV model	BATTERY CAPACITY (KWH)	BATTERY PRICE ₱ (K£)
Nissan Leaf	24	4.25
Nissan e-NV200	40	6.40
BYD e6	82	7.71

Figure. 8 illustrates the day-ahead power set points estimation according to the day-ahead EV penetration data forecast (Figure 9.).
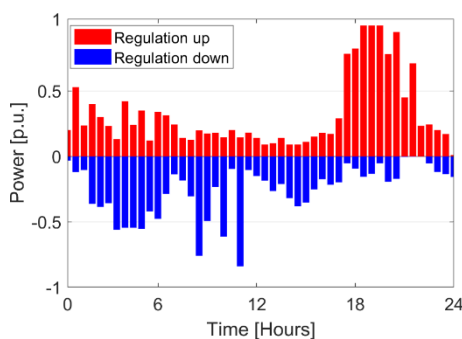

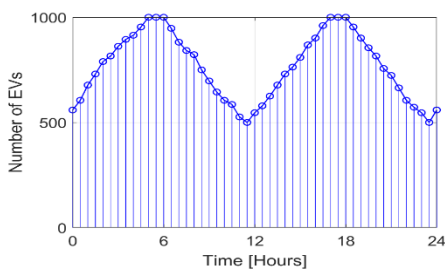FIGURE 8. Day-ahead capacity estimation schedules

FIGURE 9. Day-ahead forecast for EVs penetration

Data from [26] corresponds to the real-time regulation signal (Figure.10), and regulation up/down prices (Figure.11) for providing reliable regulation up and down.
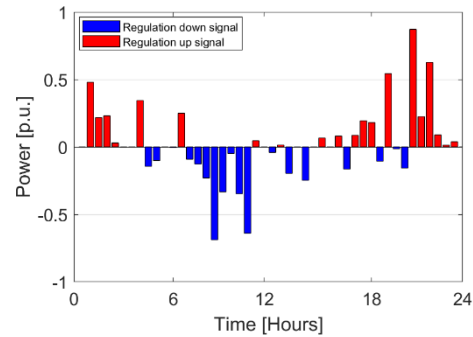

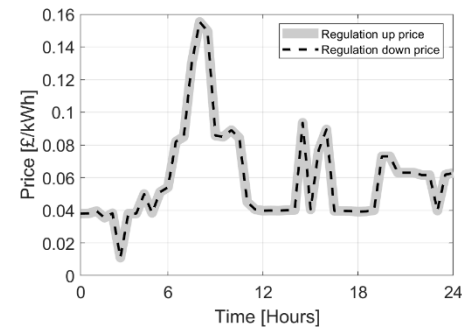FIGURE 10. A D-day regulation signal received from TSO (R^{ref})

FIGURE 11. Regulation up/down price 05 January 2017 [26]

The real-time cumulative power for regulation service by the fleet of EVs has been compared with the regulation signal sent by the TSO (Figure.12).
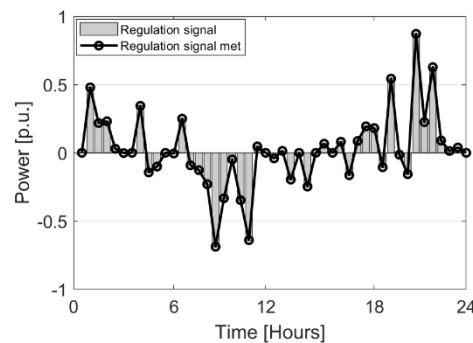

FIGURE 12. Frequency regulation support

From the results summarized in Figure 12, it is evident that the proposed scheme helps in managing the frequency fluctuations at grid level by meeting the requested reference signal from TSO. Figure 13, shows the reactive energy capacity of the aggregator, the reference signal requested by the DSO, for voltage support to the grid is shown in Figure 14. The proposed scheme validates the capability of the system to give reliable voltage support to the grid (Figure 15). Figure 16 illustrates voltage variations at node 1 depending on the day-ahead schedule. As expected, the unmanaged reactive power of the aggregator schedule would generate undervoltage

several time a day, by managing the reactive energy in the grid, the operation satisfies voltage constraints, which validates the ability of the supervision to provide jointly the frequency support and voltage support.
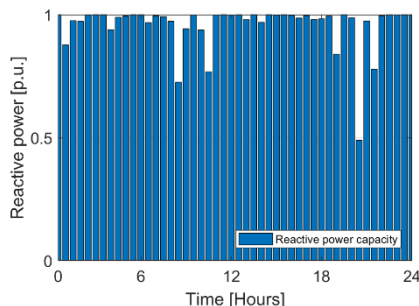

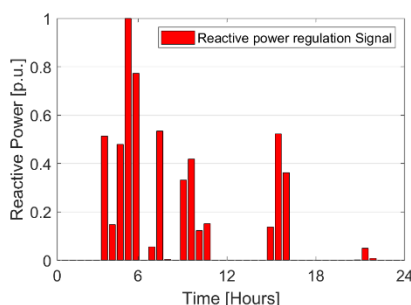FIGURE 13. *Reactive power capacity estimation*

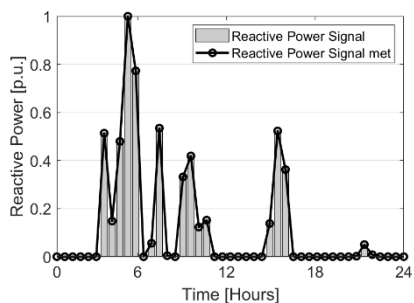FIGURE 14. **A D-day regulation signal received from DSO (Q^{ref})**

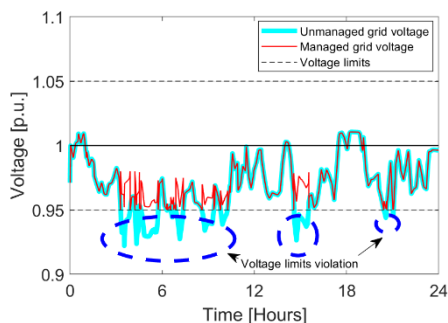FIGURE 15. **Reactive Power support**

FIGURE 16. **The voltage at node 1 (See Figure.7)**

Figure 17 shows the managed voltage dynamics at nodes 8, 15, 21, 23 and 30, corresponding to CS1, CS2, CS3, CS4 and CS5 connection points respectively. As expected, by managing the reactive energy within the grid, the operation

satisfies voltage constraints (i.e., $0.95 \, \text{p.u.} \leq V_i \leq 1.05 \, \text{p.u.}$ $i = 1:5$), at all connections points.
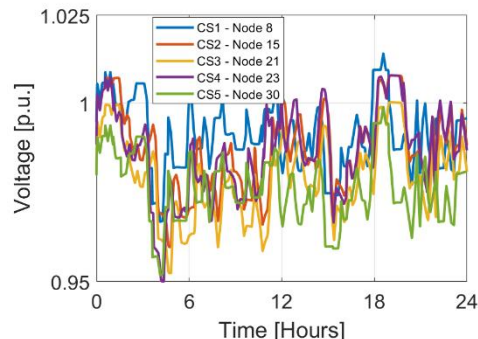

FIGURE 17. **The managed voltage variation at nodes 8,15,21,23 and30, corresponding to CS1, CS2, CS3, CS4 and CS5 connection points respectively (See Figure.7).**

Figure. 18 shows a one-day schedule for one EV, the final desired SOC, of value of 80% by the EV owner is met. Comparing the two graphs, it can be seen that the V2G profit function that ignores the battery degradation model is different from the charge and discharge method obtained by the V2G profit function simulation including the battery degradation model.
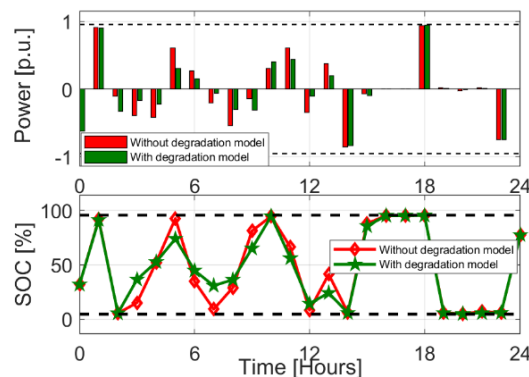

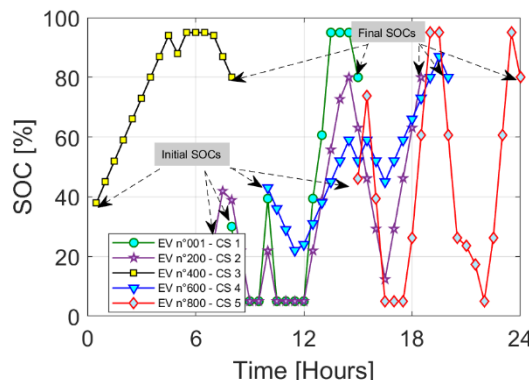FIGURE 18. **SOC and one-day schedule for an EV on the bus 15, CS2**

FIGURE 19. **Different SOCs for the EVs N°1, 200, 400, 600 and 800, plugged-in in the CS1, CS2, CS3, CS4 and CS5 respectively (See Figure.7)**

Figure. 19 shows different SOCs cases, for the EVs N°1, 200, 400, 600 and 800, plugged-in in the CS1, CS2, CS3, CS4 and

CS5 respectively. As it can be seen, the final SOCs, for all vehicles, met the final desired value of 80% by the EV owner. The significance of this result further informs the potential economic benefit associated with the integration of a battery ageing model within overall V2G optimisation schedule.

TABLE III
EV DAILY V2G OPERATION COST

EV model	WITHOUT BATTERY DEGRADATION MODEL	INCLUDING BATTERY DEGRADATION MODEL
Battery wear cost (£/day)	-0.4969	-0.4348
G2V cost (£/day)	-0.0281	-0.0276
V2G Reward (£/day)	+0.1649	+0.1431
Total Cost (£/day)	-0.3601	-0.3193

Furthermore, Table III lists the comparison of one EV operational cost between the optimisation problems with battery degradation model and the one without it. With battery degradation process considered, both the battery wear cost and the charging cost are reduced as well as the V2G reward. Therefore, it results in a decreased total operation cost when the battery degradation model is formulated in the optimisation problem.

TABLE IV
EV DAILY CHARGING COST

EV model	COST
Battery wear cost (£/day)	-0.061
Charging cost (£/day)	-1.434
Total Cost (£/day)	-1.495

The battery wear cost, the charging cost (i.e. traditional charging operation), and the total cost of the EV operations without applying the V2G strategy are given in Table IV. The table shows that, the battery loss, circa £0.061 per day from its value due to the daily charging operation, its smaller than V2G wear cost, which has an average of £0.45 per day. Figure 20 shows the comparison of the total cost between traditional charging operation and proposed V2G strategy, for one EV, which includes both with- and without- battery degradation model problem formulations. It can be observed that the charging cost can be significantly reduced by applying the proposed V2G strategy (i.e. average of £0.34 per day using V2G vs £1.49 per day without V2G). The benefits from the grid support, including both the frequency and the voltage services, with proposed V2G strategy are listed in Table V. It can be concluded, that, voltage support is more suitable for making benefits of the aggregator, while the frequency support is gainful to the EV owner, since it has reduce the charging cost.

FIGURE 20. Daily charging cost

TABLE V
DAILY AGGREGATOR GRID SUPPORT OPERATIONS BENEFIT

EV model	FREQUENCY SUPPORT	VOLTAGE SUPPORT
Daily service reward (£/day)	+1093.23	+168.49
Daily service cost (£/day)	-0999.82	0
Daily benefit (£/day)	+93.41	+168.49
Total Aggregator reward (£/day)	+261.9	

VI. CONCLUSIONS

This work presents an optimised and simplified V2G operation for a frequency and voltage support scheme based on a fleet of EVs integrated within the power grid. The system performs day-ahead scheduling and identifies the intraday schedule changes that are required or economically interesting to take various contingencies into account. The designed scheme helps in providing optimised regulation services, and also voltage regulation support to the network. EV battery degradation issues are also taken into account, while providing the necessary ancillary services. The optimisation objectives have been supported by integrating a battery degradation model, to be able to minimize the degradation cost and the charging cost through V2G operation. Further, the designed objectives have been verified with extensive simulation performed on real-time UK National Grid regulation data. The obtained results clearly indicate that the proposed scheme gives satisfying results under different conditions and is feasible to be adopted in real-time scenarios.

VII. FURTHER WORK

In the future, the authors intend to integrate the ageing model from a long-term experimental study, of lithium-ion battery within V2G operation. A further refinement of the strategy would also be to integrate an accurate prediction model, for day-ahead EV parameters estimation, by using UK EV charging dataset.

REFERENCES

[1] S. I. Vagropoulos and A. G. Bakirtzis, "Optimal bidding strategy for electric vehicle aggregators in electricity markets," IEEE Transactions on Power Systems, vol. 28, no. 4, pp. 4031–4041, Nov 2013.

[2] K. Kaur, N. Kumar and M. Singh, "Coordinated Power Control of Electric Vehicles for Grid Frequency Support: MILP-Based Hierarchical Control Design," in IEEE Transactions on Smart Grid, vol. 10, no. 3, pp. 3364-3373, May 2019.

[3] H. Liu, Y. Zhang, S. Ge, C. Gu and F. Li, "Day-Ahead Scheduling for an Electric Vehicle PV-Based Battery Swapping Station Considering the Dual Uncertainties," in *IEEE Access*, vol. 7, pp. 115625-115636, 2019.

[4] Rogers, K. M., Klump, R., Khurana, H., Aquino-Lugo, A. A., & Overbye, T. J, "An authenticated control framework for distributed voltage support on the smart grid," in *IEEE Trans Smart Grid*, 1(1), 40–47, 2010.

[5] Pavić, I., Capuder, T., & Kuzle, I. "Value of flexible electric vehicles in providing spinning reserve services", *Appl Energy*, 157(November), 60–74, 2015.

[6] Dallinger, D., Krampe, D., & Wietschel, M. (2011). Vehicle-to-grid regulation reserves based on a dynamic simulation of mobility behavior[J]. IEEE Trans Smart Grid, 2(2), 302–313.

[7] O. Kolawole and I. Al-Anbagi, "Electric Vehicles Battery Wear Cost Optimization for Frequency Regulation Support," in *IEEE Access*, vol. 7, pp. 130388-130398, 2019.

[8] Liu, H., Hu, Z., Song, Y., Wang, J., & Xie, X. (2015). Vehicle-to-grid control for supplementary frequency regulation considering charging demands. IEEE Trans Power Syst, 30(6), 3110–3119.

[9] Kisacikoglu, M.C.; Ozpineci, B.; Tolbert, L.M. Examination of a PHEV bidirectional charger for V2G reactive power compensation. In Proceedings of the 2010 25th Annual IEEE Applied Power Electronics Conference and Exposition (APEC), Palm Springs, CA, USA, 21–25 February, 2010; pp. 458–465.

[10] Kisacikoglu, M.C.; Ozpineci, B.; Tolbert, L.M. Reactive power operation analysis of a single-phase EV/PHEV bidirectional battery charger. In Proceedings of the 2011 IEEE 8th International Conference on Power Electronics and ECCE Asia (ICPE & ECCE), Jeju, Korea, 30 May–3 June 2011; pp. 585–592.

[11] K. Kaur, M. Singh and N. Kumar, "Multiobjective Optimization for Frequency Support Using Electric Vehicles: An Aggregator-Based Hierarchical Control Mechanism," in *IEEE Systems Journal*, vol. 13, no. 1, pp. 771-782, March 2019.

[12] Ran Wang, Yifan Li, Ping Wang & D. Niyato. Design of a V2G aggregator to optimize PHEV charging and frequency regulation control. In Smart Grid Communications (SmartGridComm), 2013 IEEE International Conference on, pages 127–132, Oct 2013. 23

[13] Yang Z, Yu S, Lou W, Liu C. P^2: privacy-preserving communication and precise reward architecture for V2G networks in smart grid. IEEE Trans Smart Grid 2011;2(4):697–706

[14] Su W, Rahimi-Eichi H, Zeng W, Chow M-Y. A survey on the electrification of transportation in a smart grid environment. IEEE Trans Ind Inform 2012;8(1):1–10.

[15] Letendre SE, Kempton W. The V2G concept: a new model for power?, Public Utilities Fortnightly 2002. 16–26.

[16] Fang X, Misra S, Xue G, Yang D. Smart grid – the new and improved power grid: a survey. IEEE Commun Surveys Tuts 2012;14(4):944–80

[17] W. Su, H. Eichi, W. Zeng, and M. Chow, "A survey on the electrification of transportation in a smart grid environment," IEEE Trans. Ind. Informatics, vol. 8, no. 1, pp. 1–10, Feb. 2012.

[18] Choi, Yohwan; Kim, Hongseok. 2016. "Optimal Scheduling of Energy Storage System for Self-Sustainable Base Station Operation Considering Battery Wear-Out Cost." Energies 9, no. 6: 462.

[19] J. Wang, G. R. Bharati, S. Paudyal, O. Ceylan, B. P. Bhattarai and K. S. Myers, "Coordinated Electric Vehicle Charging with Reactive Power Support to Distribution Grids," in IEEE Transactions on Industrial Informatics.

[20] Han, S.; Han, S.; Aki, H. A practical battery wear model for electric vehicle charging applications. Appl. Energy 2014, 113, 1100–1108.

[21] G. D. Yalcin and N. Erginel, "Determining weights in multiobjective linear programming under fuzziness," in Proceedings of the World Congress on Engineering, vol. 2, 2011, pp. 6–8.

[22] A. Alsabbagh, H. Yin and C. Ma, "Distributed Electric Vehicles Charging Management with Social Contribution Concept," in IEEE Transactions on Industrial Informatics.

[23] N. I. Nimalsiri, C. P. Mediwaththe, E. L. Ratnam, M. Shaw, D. B. Smith and S. K. Halgamuge, "A Survey of Algorithms for Distributed Charging Control of Electric Vehicles in Smart Grid," in IEEE Transactions on Intelligent Transportation Systems.

[24] I. Duggal and B. Venkatesh, "Short-term scheduling of thermal generators and battery storage with depth of discharge-based cost model," IEEE Transactions on Power Systems, vol. 30, no. 4, pp. 2110–2118, 2015.

[25] Baran M. E., WU F. F., Network reconfiguration in distribution systems for loss reduction and load balancing, IEEE Transactions on Power Delivery, 1989, 4(2), p. 1401-1407.

[26] Elexon: 'System sell and buy prices'. Available at https://www.bmreports.com/bmrs/?q=balancing/systemsellbuyprices

[27] S. Minniti, A. N. M. M. Haque, N. G. Paterakis and P. H. Nguyen, "A Hybrid Robust-Stochastic Approach for the Day-Ahead Scheduling of an EV Aggregator," 2019 IEEE Milan PowerTech, Milan, Italy, 2019, pp. 1-6.

[28] Xinzhou Li, Yitong Tan, Xinxin Liu, Qiangqiang Liao, Bo Sun, Guangyu Cao, Cheng Li, Xiu Yang, Zhiqin Wang, "A cost-benefit analysis of V2G electric vehicles supporting peak shaving in Shanghai", *Electric Power Systems Research*, Volume 179, 2020, 106058.

[29] Sasan Pirouzi, Jamshid Aghaei, Vahid Vahidinasab, Taher Niknam, Amin Khodaei, "Robust linear architecture for active/reactive power scheduling of EV integrated smart distribution networks", Electric Power Systems Research, Volume 155, 2018, Pages 8-20,

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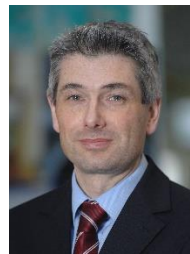
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