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Dynamic pricing and control for EV charging stations with solar generation

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ABSTRACT

Demand response is one of the most promising tools for smart grids to integrate more renewable energy sources. One critical challenge to overcome is how to establish pricing and control strategies for integrating more electric vehicles (EVs) and renewable energy sources. This paper proposes a dynamic optimal operation of a solar-powered EV charging station where onsite solar generation, number of EVs in the system, historical EV response to price, EV technical specifications and EV driving behaviour vary. A bi-level optimisation approach is proposed, where pricing tariffs ensure an economic and price responsive operation, then EV charging schedules are computed for energy bidding capacity to provide balancing services. Simulations are conduced to evaluate the performance of unidirectional and bidirectional EV charging at different charging speeds and demand elasticity. Results demonstrate the potential of extra revenue streams coming from the participation in energy markets compared to that of EV charging alone. Additionally, limitations of energy bidding with battery size, trip requirements and charging ratings are discussed to show insights into the operation of charging stations.

1. Introduction

As the transportation sector moves towards the replacement of the combustion engine with an electric one, the power sector also moves from high-carbon emission energy generation sources to low-carbon emission ones, such as wind, solar and biomass energy. However, this transition brings significant challenges to power systems' reliability and resilience due to the increasing complexity of balancing energy demand and supply [1]. This increasing complexity could come from both intermittent renewable energy sources and increasing power demand, for instance as a result of more electric vehicles (EVs) [2]. Consequently, more frequent control requirements and reformed ancillary services provision are required to improve and maintain the operations of power networks [3,4]. The development of EV charging technology and demand response programs bring an opportunity to aggregate EVs' power demand to participate in current and emerging energy markets, which facilitate the transition to decarbonisation of the transportation sector [5–7].

Recent innovation projects have proposed to use the flexibility of EV charging for participating in energy markets to benefit from EV batteries to the grid. Vehicle to grid (V2G) technology allows EVs to discharge electricity back to the power grid given the bidirectional power flow capability. The report [8] explored projects with V2G technology and noted that only one project is currently at commercialisation stage. Some ongoing projects aim to test for the feasibility of V2G support to the network, e.g., the new Electric Nation V2G trial in Wales, UK [9]. There still exists research gaps for integrating EVs with the power grid, for example, efficient demand response of EVs and smart charging strategies at charging stations.

Recent research has shown the advances in energy bidding and pricing depending on market designs and the business models of the charging station operator: Sortomme et al. [10] designed a bidding mechanism to model all possible V2G capability for frequency regulation and spinning reserves to maximise charging operator revenues. Nakano et al. [11] proposed aggregation of EVs and plug-in hybrid vehicles using a home energy management system for residential households to participate in a regulation market with different time scale control mechanisms. Mizuta et al. [12] proposed a model for balancing services at the distribution level to mitigate voltage imbalance using ordinary differential equations to represent distribution voltage. Data uncertainties when aggregating EVs for balancing services have also been considered using bias measurements of regulation signals as proposed by Cui et al. [13] and pricing regulation predictions using seasonal auto regressive integral moving average model as proposed by [14]. These research works have provided contributions in terms of control for energy bidding of EVs parked in residential locations and uncertainties in the system; however, pricing mechanisms that

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engage customers in balancing services have not been considered, nor have the stochastic behaviour and demand response nature of EVs been explored.

In order to influence customers according to grid requirements, demand response programs have been used as promising tools to enhance penetration of more renewable energy sources in the grid, while encouraging certain patterns in customer energy demand [15,16]. Following forecasting of market clearing price and ancillary service prices, Chandra Mouli et al. [17] proposed aggregation of EVs parked in buildings integrated with solar panels to maximise the charging operator revenues. Lui et al. [18] proposed a dynamic pricing model for an EV aggregator using a reinforcement learning algorithm that considers updates from a spot market, price elasticity from users to compute energy prices and EV load changes. Tawfiq Masad et al. [19] proposed a real time pricing scheme using inverse demand curve to account for price changes when microgrids are congested. Chen et al. [20] proposed pricing schemes using cooperative and non-cooperative game formulations in order to achieve market equilibria. These works have adequately considered how EV schedules can be adapted to pricing signals set by the charging station operator. However, prices for auction markets have not been explored; and pricing to influence driver behaviour and charging responses to price changes have not been effectively considered.

To continue with research in demand side management mechanisms that aim to influence EV user demand and/or improve EV charging service, Li et al. [21] proposed using congestion pricing and waiting time options to EV users to model geospatial charging via a navigation system. Hou et al. [22] proposed using short term and long term contracts, as well as time of use tariffs and price discounts to shape EV charging scheduling. Zhang et al. [23] proposed another pricing mechanism to incentivise coordination in EV charging stations and minimise service dropping rate modelled in a queuing system. Similarly, Zhao et al. [24] modelled charging stations using queue theory to create pricing scheme to maximise quality of service of charging stations. In terms of EV consideration of user preferences for charging, Selim et al. [25] proposed using charging price preferences of EV users following real time electricity price to compute EV charging scheduling. These works adequately modelled pricing and incentive mechanisms to shape smart charging schemes and ensure charging coordination. However, they did not consider pricing mechanisms for vehicle to grid capability of EV battery integration with ancillary services and the respective pricing mechanisms for auction bids programs such as the ones used in the UK. As described before, there are critical research gaps in pricing schemes for balancing services offered by EV charging as there is limited research that has integrated engaging pricing for EV discharging considering EV users expected responses to price.

In addition, financial modelling represents one of the biggest barriers to the commercialisation of V2G technology [8] even though flexibility potentials with this technology are higher than with G2V technology only. To address the aforementioned challenges and research gaps, this paper proposes a dynamic, customer responsive pricing scheme for commercial charging stations with onsite solar generation. This pricing scheme can be used in auction based markets, where charging operators send price and energy bidding information to grid operators. This paper offers the following key contributions:

- A novel dynamic pricing scheme is developed to create a tariff that changes using grid analytics from historical EV user responses to price and maximisation of revenues from the charging station. Key variables for economical operation of the charging operator consider onsite solar generation profitable financial relationships and EV users charging availability to set bid aggregation for ancillary service provision
  This scheme provides an economical and customer engaging solution that addresses the pricing dilemma for EV charging, profitable incentives to increase or decrease charging rate, and auction bidding prices for participating in balancing services.

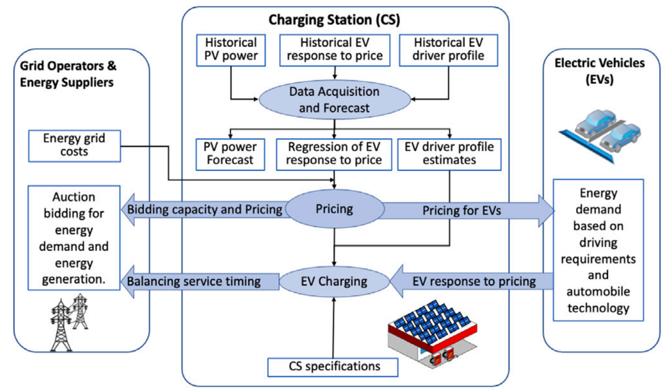

Fig. 1. Proposed bi-level optimisation model with activities and communication between stakeholders involved and variable inputs for the pricing and EV charging optimisation modules.

- A new bi-level optimisation approach is proposed for managing pricing and control mechanisms for EV charging and integration energy bids with ancillary services. Compared to other pricing mechanisms such as stackelberg approaches, separation of pricing and EV charging control offer a more applicable and realistic method where price equilibrium could be imposed externally by independent energy regulator. Pricing is the first optimisation module to set pricing from the charging station operator, aiming to have additional revenue streams to EV charging when participating in balancing services. Then, the EV charging module is the second optimisation that estimates an optimal charging rate from the EV user's perspective, following the pricing signals while meeting customer and charging technology restrictions.
- A new control strategy to plan the stochastic EV charging bids combined with EV charging scheduling is proposed to manage unidirectional grid to vehicle (G2V) and bidirectional V2G charging technologies. It provides potential revenue streams and energy bidding capability to support balancing services. This control strategy is able to handle probabilistic arrivals, departures, trip requirements, EV user availability, battery size restrictions and varying charging rates.

The remaining parts of this paper are organised as follows. The proposed model is introduced in Section 2, including the dynamic pricing scheme and EV charging control compliant with V2G and G2V technologies. Section 3 shows simulation setup, and then the simulation results of proposed schemes are evaluated. Discussions and conclusions are presented in Section 4.

2. Proposed model

The proposed model consists of an EV aggregator or charging station operator of a group of EVs with connection to the transmission or distribution system operator. Fig. 1 summarises the activities and exchange of messages for the operation of the charging station participating in balancing services when using EVs as flexible loads. It also presents the bi-level optimisation approach used by the charging operator. The EV aggregator could be the owner of the charging station that is capable of buying electricity from the grid, of producing onsite solar generation, of selling/buying electricity to EV users and of selling energy to the grid for balancing services provision. With the use of Information and Communication Technologies, the EV aggregator can know in advance important information for the charging station operation such as EV drivers response to price, arrivals, departures, trip requirements and solar power forecast.

This information is used as a data driven approach for estimation of price strategies that maximise revenues based on historical customer response to price during a day. Given the price optimisation, energy bidding coming from EVs is estimated using a control optimisation that evaluates demand response of EV drivers. Finally, the potential revenues from V2G and G2V charging technology are presented to comprehend EV driver response to prices given a predetermined dynamic pricing strategy.

The business model of the charging station operator proposed in this paper is applicable for big parking lots such as the ones in office buildings or supermarkets. The revenues of the charging station operator come from charging of EVs and from participating in balancing grid services. The three stakeholders involved are charging station operator, grid operator and EV customers, as shown in Fig. 1. One example of the grid operator is National Grid which is the transmission system operator in the UK. Firstly, the charging station process expected estimates; response to price from EVs, EV driver profile and solar power for the following day. Secondly, this information is then used in the first optimisation; dynamic time of use pricing which uses a regression analysis of price and charging quantities for EV charging to maximise revenue curves by using Calculus, a popular approach used in microeconomics. This optimisation uses cost, demand response estimates, and economic boundaries to estimate pricing for EV charging and for ancillary services. Thirdly, the charging operator uses the second optimisation that is the EV charging, formulated with linear programming. This optimisation estimates EV charging scheduling charging strategies assuming customers will respond to price signals by charging when energy is cheaper and as long as restrictions, e.g., charging availability, driving requirements, charging and battery limits, are ensured. Finally, the outputs from the second optimisation are then used by the charging operator to charge EVs and aggregate energy bids for ancillary services. The two modules in the bi-level optimisation are explained in more detail in the following subsections.

2.1. Time of use dynamic pricing

The pricing module is the first part of the model where prices is created when learning from historical price information. This price methodology uses the fundamentals of microeconomics of a monopoly where the EV aggregator is able to set prices and EV users are price takers. The model uses the information of price and demand curves, energy costs from the grid and stochastic onsite solar generation to use for EV charging, for every hour in a day. A time of use pricing tariff approach is proposed to encourage EV charging behaviour response from price differences in time with more expensive and cheaper prices. When looking closely at the stochastic variables of the model, i.e., the number of EVs in the charging station and variation of solar generation, the pricing model is able to compute a dynamic behaviour of the tariff results for both pricing to announce to EV users and to a grid operator. Thus, a combination of dynamic and time of use tariff is used to encourage charging shifts to timings where ancillary services occur and when energy is cheaper for the charging station operator. These pricing outputs of the model are computed to make the operation of charging station economically feasible and to optimise revenues. The formulation of the pricing module considers the study of an average EV user i and changes in the dynamics of the charging station in time t. The main goal of the EV aggregator in (1) is to find the optimum values of quantity Q_t^* that will maximise utilities u_t when evaluating revenues r_t and costs c_t for every hour in a day as follows

$$\underset{Q_t}{\text{Max}}\ u_t(Q_t) = r_t(Q_t) - c_t(Q_t). \tag{1}$$

The utilities are subject to the revenues at hour t estimated by

$$r_t(Q_t) = p_t(Q_t) \cdot Q_t. \tag{2}$$

The inputs for revenues are historical price p_t and energy demand Q_t. To optimise for an optimum quantity, price is computed as a function of quantity from historical EV customer response to price represented as a linear regression by

$$p_t(Q_t) = \beta_{0t} + \beta_{1t} \cdot Q_t, \tag{3}$$

where β_{0t} and β_{1t} are the corresponding coefficients from predicted price and charging demand estimations. The principles of this linear regression relationship which are based on microeconomic theory [26, 27] are key in the pricing scheme proposed to estimate better demand response pricing strategies. Microeconomic fundamentals are used in this paper to measure predicted customer response to price from variations of historical charging demand and costs in a day.

The costs in (1) are computed from the cost of the charging station per energy unit to buy from the grid cg_t and taking into account the available onsite solar power generation Ps_t per solar panel n, that can be used for charging available EVs at the charging station as below

$$c_t(Q_t) = cg_t \cdot (Q_t - n \cdot Ps_t). \tag{4}$$

EV availability is studied as the available time av_t. An EV can be charged from arrival ar to departure de at the charging station according to EV driver behaviour in time t. Thus the availability of each EV is defined by

$$av_t = \begin{cases} 1, & \text{if } ar \le t \le de \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

To find an optimal charging demand Q_t^* from (1), following price and charging demand optimisation principles of microeconomic theory, it is required to equal marginal revenue r_t' and marginal cost c_t' as follows

$$Q_t^* = arg(r_t' - c_t' = 0). \tag{6}$$

With some rearrangements as detailed in Appendix, we can find this optimal energy demand quantity as below

$$Q_t^* = (cg_t - \beta_{0t})/(2 \cdot \beta_{1t}). \tag{7}$$

Given the optimal charging demand, we obtain the optimal price from the linear regression function estimated from historical demand as below

$$p_t^* = \beta_{0t} + \beta_{1t} \cdot Q_t^*. \tag{8}$$

As the charging operator aims to have an additional revenue stream to charging EVs which is obtained from bidding energy for balancing services, definition of both profitable prices and charging rating limits is key. Thus, if we define charging ratings as charging demand turn down as Qd_t, and demand turn up as Qu_t, the required charging ratings to have positive utilities must be within the following boundaries

$$Qd_t \le Q_t^* - \min(x_t), \tag{9}$$

$$Qu_t \le \max(x_t) - Q_t^*, \tag{10}$$

where $\min(x_t)$ and $\max(x_t)$ state the minimum and maximum energy limits so that utility function $u_t(Q_t)$ is positive. Thus, these two quantity boundaries can be estimated from solving $u_t(Q_t) = 0$. To illustrate these boundaries, Fig. 2 shows an example of the positions of $\min(x_t)$, $\max(x_t)$ and Q_t^* in a price per energy unit (p/kWh) and charging demand (kWh) graph that also shows their relation to functions of utilities, revenues, cost and the inverse demand curve.

To compute the demand response prices for the time of use dynamic tariff, the same linear regression for the optimum price is used. For practicality, energy balancing services when influencing EVs to charge more energy are referred as energy turn up, and energy turn down when influencing EVs to charge less energy or discharge energy with V2G technology. Calculations are made to find a profitable maximum and a minimum demand relation to price to provide incentives to EV customers. Prices for either energy turn down (pd_t) or energy turn up (pu_t) are estimated as follows

$$pd_t = \beta_{0t} + \beta_{1t} \cdot (Q_t^* - Qd_t) \tag{11}$$

$$pu_t = \beta_{0t} + \beta_{1t} \cdot (Q_t^* + Qu_t). \tag{12}$$

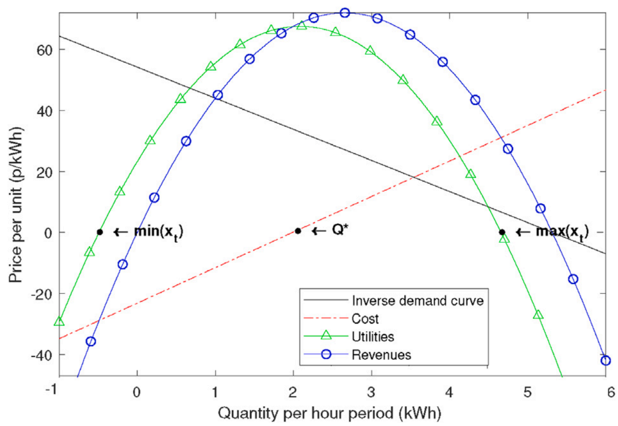

Fig. 2. Mathematical relationship of variables in pricing optimisation.

The pricing matrix for the time of use dynamic tariff is computed from a combination of the optimum price and demand response prices, whenever is more convenient for the charging station to provide balancing services in a day, according to a charging station utilisation parameter ρ_t. The final price matrix (pf) is given by

$$pf = \begin{bmatrix} p_1^* & \dots & p_{ti-1}^* & pd_{ti} & \dots & pd_{tf} \\ \dots & pu_{tj} & \dots & pu_{te} & p_{te+1}^* & \dots & p_{24}^* \end{bmatrix}, \tag{13}$$

which is integrated from the optimum price (p_t^*) since the start of the day and before the time where energy turn down starts at $ti-1$, then pd_t and pu_t prices are integrated accordingly to then go back to the optimal tariff from the end of the energy turn up period at $tf+1$, and until the end of the day.

Utilisation parameter from the hourly capacity (ρ_t) of the charging station is considered in order to decide which timings are better for either providing energy turn down or energy turn up. The utilisation is classified in high (h_t), medium (m_t) and low (l_t) based on the charging availability between arrival and departure of EVs regardless of their charging status. Balancing services are provided only when capacity at the charging station is at high levels because the availability of EVs at the charging station is key to provide the corresponding flexibility services. The number of hourly periods at high level is divided by two periods with priority of providing cheaper tariffs to customer. For instance if there are 7 periods of time where there are parking spaces occupied with capacity greater than 2/3, then there are 3 time periods for energy turn down (higher prices) and 4 time periods for energy turn up (lower prices). Thus utilisation at the charging station is estimated by

$$2/3 \cdot \rho_t \leq h_t \leq \rho_t \tag{14}$$

$$1/3 \cdot \rho_t \leq m_t \leq \rho_t \cdot 2/3 \tag{15}$$

$$0.1 \cdot \rho_t \leq l_t \leq \rho_t \cdot 1/3. \tag{16}$$

The next stage for pricing calculation is the computation of prices for participation in balancing services in auction mechanisms, for instance the ones to announce to National Grid in the UK. Flexibility service companies are expected to provide price, capacity and timings for energy turn down or energy turn up provision [28]. Given the structure of the market, the EV aggregator is able to provide prices and bidding quantities. The expectation is that balancing services are used as additional revenue streams. Consequently, the utilities obtained from Grid Operator should balance the loss of revenues of EV charging when using the demand response prices pd_t and pu_t, in other words when deviating from the optimum price and quantity. Therefore, prices to announce to Grid Operator are computed based on equivalent revenue deviations from the optimal revenue from EV charging. The price estimation is computed from making equal optimum utilities (u_t^*) and expected utilities to obtained from Grid Operator for energy turn down (u_{1t}) and energy turn up (u_{2t}) as below

$$u_t^* = u_{1t} \tag{17}$$

$$u_t^* = u_{2t}, \tag{18}$$

where utility functions for energy demand turn down and turn up can be given by

$$u_{1t} = \begin{cases} pgd_t \cdot |Qd_t| - pd_t \cdot |Qd_t|, & \text{if } Qd_t \leq 0 \\ pgd_t \cdot Qd_t - cg_t \cdot (Qd_t - n \cdot Ps_t), & \text{otherwise} \end{cases} \tag{19}$$

$$u_{2t} = pgu_t \cdot Qu_t - cg_t \cdot (Qu_t - n \cdot Ps_t). \tag{20}$$

The costs for energy turn down in (19) vary when it is economically possible to discharge an EV, in this case the corresponding costs are energy paid to EV users. In the case when the charging rate is positive, costs are estimated according to grid energy costs and available solar power at the charging station.

Thus, the prices for bidding energy for balancing services of energy turn down pgd_t and energy turn up pgu_t are computed as follows

$$pgd_t = \begin{cases} \frac{u_t(Q_t^*)+pd_t \cdot |Qd_t|}{|Qd_t|}(1+\delta), & \text{if } Qd_t \leq 0 \\ \frac{u_t(Q_t^*)+cg_t \cdot (Qd_t - n \cdot Ps_t)}{Qd_t}(1+\delta), & \text{otherwise} \end{cases} \tag{21}$$

$$pgu_t = \frac{u_t(Q_t^*) + cg_t \cdot (Qu_t - n \cdot Ps_t)}{Qu_t}(1+\delta). \tag{22}$$

The calculations of these prices are obtained when solving for pgd_t and pgu_t from the substitution of (19) and (20), in (17) and (18). To allow a profit from participating in balancing services, a margin of utility δ is added to Grid Operator prices pgd_t and pgu_t to cover for additional complexities of management control. This is a reasonable addition to pricing because the charging station sets prices for bidding in an auction market considering a cost based strategy.

2.2. EV's charging control

The control strategy which is used for planning of energy bids to submit to the grid operator (e.g., National Grid), is constructed to follow pricing signals received from the charging station operator in a day ahead timeline, by minimising costs from charging an EV. The control strategy, which was initially inspired by the work of Sortomme et al. [29], has been adapted to be able to work with different charging rates limits, battery state of charge (SOC) restrictions and stochastic variables for EV requirements. These additions allow accurate simulations of driver behaviour during a day with different charging capabilities. The objective function of the charging control is the minimisation of costs (c_i) for the complete charging period the ith EV parked at the charging station given by

$$\underset{q_{i,t}^*}{\text{Min}}\ c_i = \sum_{t=1}^{T} pf \cdot q_{i,t}, \tag{23}$$

where the charging rate q_t^* is the decision variable in the formulation that determines the charging schedule of each EV every hour. This decision variable can become negative and discharge the EV battery when the charging station aims to provide balancing services to the grid and when the EV is conveniently available for discharging. It is expected that EVs will get not only positive values from the costs in the objective function but also negative values (EV revenues) when getting paid for V2G provision if allowed.

To meet technology constraints of the charging station and the EV, we define the charging rate limits for the charging schedule with a_t, as the maximum charging rate and b_t, as the minimum charging rate of q_t

when evaluating the charging rate of an EV (y_t) and charging rate of the charging station pole (z_t) as below

$$a_{i,t} = \min(y_{i,t}, z_{i,t}), \tag{24}$$

$$b_{i,t} = \max(-y_{i,t}, -z_{i,t}). \tag{25}$$

The state of charge of the EV is also considered, where $soc_{i,t}$ is ith EV's battery state of charge at time t that considers charging efficiency ef when charging rate is positive $q^+_{i,t}$ or negative $q^-_{i,t}$ as follows

$$soc_{i,t} = soc_{i,t-1} + q^+_{i,t} \cdot ef + q^-_{i,t} \cdot (2 - ef) \tag{26}$$

Note that efficiency is modelled from the charging operator perspective, where it has to charge more energy, and discharge less energy to avoid taking advantage of EV users over payment charges, and to balance power losses. For instance, for 7.2 kW charge with 0.9 of charging efficiency, the charging operator should provide charging of 10% more of 7.2 kW, and for discharging, the charging rate should be 10% less charge than the optimum charging rate metered in the charging station pole. Consequently, charging optimisation limits $q_{i,t}$ are subject to

$$\begin{cases} q_{i,t} \geq b_{i,t} \cdot av_{i,t}, & \text{if } q_{i,t} \leq 0 \\ q_{i,t} \leq a_{i,t} \cdot av_{i,t}, & \text{if } q_{i,t} > 0 \end{cases} \tag{27}$$

where $av_{i,t} = \{0 \text{ or } 1\}$ is a binary matrix per EV that states its availability (arrival to departure) at the charging station as described in the pricing optimisation. The usage of the charging rate limits in (27) allow the modelling of charging and discharging constraints for specific periods of time and thus, allow the modelling of V2G and G2V technology. Battery size limits w_i are ensured by taking into account the state of charge of an EV by

$$0.01 \cdot w_i \leq soc_{i,t} \leq w_i. \tag{28}$$

EV trip requirements are formulated when calculating state of charge (energy levels) by

$$trip_i = socf_i - soci_i, \tag{29}$$

where $soci$ is the initial state of charge and $socf$ is the final state of charge of an EV.

2.3. Vehicle to grid and grid to vehicle analysis

To evaluate potential utilities from the price strategy proposed in the time of use dynamic pricing subsection, the responses to prices from EV drivers described in the EV charging control subsection are evaluated against V2G (bidirectional) and G2V (unidirectional) technology. As described before, the EV charging control optimisation can evaluate charging rate restrictions for both unidirectional and bidirectional charging. Thus, given the different charging rate of the EVs, revenues and costs vary as well as the interactions with the available solar power generation at the charging station. The time of use dynamic tariff can be used for testing EV driver response according to current technology available in the market.

Revenues with V2G technology capability (r_{vg}) are integrated from sales coming from aggregated bidding for energy turn up (first term), energy turn down (second term) and EV charging (third term) when the charging rate is positive (q^+_t) by

$$r_{vg} = \sum_{i=1}^{I} \left\{ \sum_{t=tj}^{te} pgu_t \cdot q_{i,t} + \sum_{t=ti}^{tf} pgd_t \cdot q_{i,t} + \sum_{t=1}^{24} pf \cdot q^+_{i,t} \right\}, \tag{30}$$

where I is the set of EVs to be charged by the charging station operator. Balancing service timings are defined by an initial hour tj and ti, and final hour te and tf for energy turn up and turn down periods respectively. Costs for providing balancing services with V2G technology capability come from energy paid to EV users when the charging rate is negative ($q^-_{i,t}$), and when energy must be bought from the grid ($q^+_{i,t}$) when referencing to available solar power generation at the charging station as below

$$c_{vg} = \sum_{i=1}^{I} \left\{ \sum_{t=1}^{24} pf \cdot |q^-_{i,t}| + \sum_{t=1}^{24} cg_t \cdot (q^+_{i,t} - P_{i,t}) \right\}, \tag{31}$$

where $P_{i,t}$ is the average available solar energy that can be used to charge an EV which can be estimated by

$$P_{i,t} = n \cdot Ps_t / \sum_{i=1}^{I} av_{i,t}. \tag{32}$$

In contrast, revenues from provision of balancing services with G2V technology capability come from sales from energy turn up and sales from EV charging by

$$r_{gv} = \sum_{i=1}^{I} \left\{ \sum_{t=tj}^{te} pgu_t \cdot q_{i,t} + \sum_{t=1}^{24} pf \cdot q_{i,t} \right\}. \tag{33}$$

Compared to V2G technology costs, G2V costs come only from buying energy from the grid when needed as below

$$c_{gv} = \sum_{i=1}^{I} \sum_{t=1}^{24} cg_t \cdot (q_{i,t} - P_{i,t}). \tag{34}$$

3. Case studies and evaluations

3.1. Simulation setup

Table 1 summarises the simulation parameters. To test the time of use dynamic pricing and the EV charging control optimisation algorithms, different cases are proposed to show applicability of the model to real case scenarios and to compare EV charging business models with balancing services. As the charging speed rating increases with EV charging types, the price for providing energy may also increase. In addition, customers may respond to prices differently, for example when there is competition in an area or when EV drivers change charging behaviour. To take into account these possibilities, the pricing strategies are evaluated with different elasticities of three inverse demand curves; an original demand from real data, a theoretical more elastic and a more inelastic demand. The original demand curve is also used to create demand curves when testing for increasing charging rates. The EV charging control strategy is used to test EV responses to

Table 1
Simulation parameters.

Parameter	Value
Charging station size	35 EVs
Time periods in a day	24, for every hour
EV arrivals	$ar \sim \mathcal{N}(\mu = 8, \sigma^2 = 1)$ [30]
EV sojourn time	$ts \sim Logistic(\mu = 0.27, s = 0.06), mn = 5, mx = 18.52$ [30]
Solar panel rating	4 kW [31]
Number of solar panels	70
Initial state of charge	Empirical cdf [32]
Trip requirements	Empirical cdf [32]
Fast charging 1, 2 and rapid ratings	7, 22 and 50 kW [33]
Mitsubishi Outlander charging ratings/battery size	3.7 and 22 kW/ 12 kWh [34]
Nissan Leaf charging rating/battery size	6.6 and 50 kW/40 kWh [35]
BMW 330e charging ratings/battery size	3.7 kW/12 kWh [36]
Tesla 3 charging ratings/battery size	11 and 100 kW/60 kWh [37]
Electricity price	10 p/kWh [38]
Utility from balancing services	10%

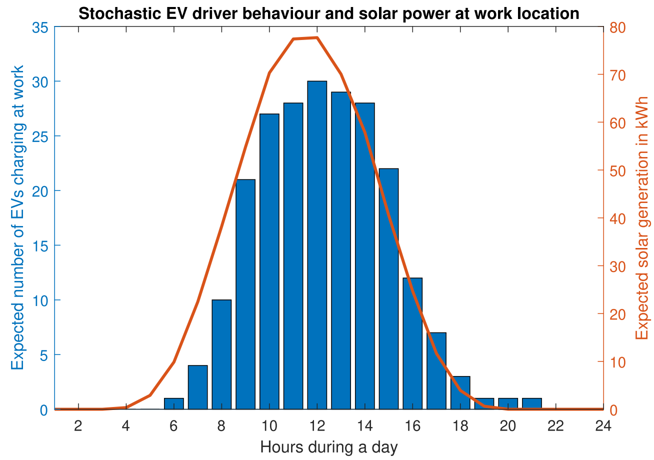

Fig. 3. Stochastic number of EVs and average hourly solar power generation with PV system at the charging station for workplace location.

prices and energy bidding capacity, the results are evaluated comparing the capability of V2G and G2V technology.

EV driver behaviour was generated from real world projects to provide accurate simulations. Fig. 3 shows stochastic number of EVs available for charging from an aggregated availability matrix of all EVs for the specific case of charging at work. This figure was generated considering a total of 35 EVs. For simulation purposes, EV profiles are created with 30, 35 and 25 EVs that arrive at the charging station in a 24 h period assuming demand changes from an original, more elastic and more inelastic demand curves respectively. The EV profiles were created from EV arrivals (ar) and sojourn timings (ts), defined as departure minus arrival time, from the work analysed by Develder et al. [30]. The available onsite power generation forecast of all seasons and the size of the solar system adopt the data from [31]. Average hourly variations of solar power variations were included to account for intermittency of solar generation during a day as it also can be observed in Fig. 3 where EV availability for work location overlaps considerably with solar generation in a day. As seasonal changes of solar power accounted for small changes in price, for practicality, average hourly seasonal solar power generation in the Northeast of UK was analysed. However, this paper propose to forecast EV behaviour and solar power generation with prediction algorithms such as ARIMA, neural networks, day ahead, etc. Definitions for initial state of charge of EVs and trips were estimated with empirical distribution functions using EV charging data of the workplace cluster information from "My Electric Avenue" project [32], kindly provided by EA technology. Charging rate limits for both the charging station and EVs use two selected charging rates of fast charging and one from rapid charging as explored in [33]. The percentage mix of EVs in the simulation used parameters of charging rates and battery size of Mitsubishi Outlander PHEV (40%), Nissan leaf (30%), BMW 330e (20%) and Tesla 3 (20%).

The demand and price curves were estimated with 40 observations with results showing significant coefficients with a p value close to zero of the linear regression model and an adjusted R-squared value of 0.815. Raw data for these calculations were estimated using real data from trial 3 of "Electric Nation" project [39], also provided by EA Technology. To estimate elasticity variations to price from EV drivers, the coefficients in the demand curve were decreased and increased by a third in order to create a more elastic and more inelastic demand curves. Prices and demand data sets for different charging rates were multiplied by 1/2 (fast charging 2), 2/3 (rapid charging) for price, and by 4 (fast charging 2), 10 (rapid charging) for demand in order to match prices close to real data in the current market available in [40]. The cost for energy from the grid was assumed to be fixed at a rate of 10 p/kWh (pence per kilowatt hour) as proposed in [38]. Once the profiles for driver behaviour, PV forecast and demand curves are created, the pricing and EV charging optimisations are used to compute results for the cases where demand curve elasticity changes as well as charging speed varies with V2G and G2V technology. Analysis and discussion of results are presented in the next two subsections.

3.2. Pricing with stochastic variables

The merits of the pricing and EV charging algorithm are evaluated in this subsection to show their potential usage in different EV driver demand response behaviour with three different elasticity levels of inverse demand curves and different charging technology with three charging speeds and V2G/G2V capabilities. The contributions towards carbon neutrality in this section can be observed in the slight differences of dynamic time of use tariff proposed EV charging and in the bidding potential from low carbon technologies coming from EV batteries as these are integrated in balancing services. First, solar power contribution towards the charging station is reflected in EV charging price, where charging schedules follow pricing signals established by the charging station. Second, carbon emissions savings coming form participating in ancillary services could be compared to the related carbon emissions in the technologies used for balancing mechanisms. Being coal and gas the most used technologies for this purpose for instance in the UK [41], carbon emission savings can vary based on EV availability, carbon grid factor, charging rating, and in the technology used for balancing services. In the best case carbon savings could be up to 573.6 CO_2eq emissions per kWh when comparing equivalence of coal (820 CO_2eq/kWh) against the lowest carbon grid factor intensity (e.g July 3, 2022 was 222.4 CO_2eq/kWh) used for EV charging and related impact of storage CO_2eq technologies (24 CO_2eq/kWh).

Fig. 4 is a representation of the basic functions used for calculation of the different pricing strategies that include an inverse demand curve, revenues, costs and utilities. The original inverse demand curves for the fast charging 1, fast charging 2 and rapid charging scenarios present the different responses to prices from an average EV at any time. The three inverse demand curves show that as prices increase per kWh, EVs would respond with charging less energy and as price decreases EVs would aim to charge more energy. The figure also shows more average revenues and utilities are obtained from rapid charging compared to fast charging 2, and more with fast charging 2 compared to fast charging 1. An explanation of this trend is a result of using higher prices and quantities with faster services of EV charging. The costs for the three charging ratings remain the same as the three cases assume the same fixed energy cost per energy unit and the same available free energy from onsite solar generation power to charge EVs.

The proposed time of use dynamic tariff in this paper includes tariffs for periods of peak, off peak and normal hours. Peak and off peak periods during a day are intended to be synchronised with timings for balancing services for energy turn down and energy turn up requirements, other timings are irrelevant for balancing services purposes. Fig. 5 shows that in the cases of the original demand curve, from 9:00 to 11:00 h energy is more expensive and from 12:00 to 14:00 h energy is cheaper. Timings with the more elastic curve are increased by one hour when energy is cheaper compared to timings with the original curve. Timings with the more inelastic curve are reduced by one hour in both expensive and cheap timings compared to timings with the original curve. The reason for these changes are related to availability of demand with different EV numbers determined by price elasticity where balancing timings are set when there is sufficient capacity at the charging station as established by the pricing algorithm. The three cases where energy is obtained with an original curve, a more elastic and more inelastic curve aim to represent changes from demand. This is an essential consideration for demand response mechanisms, because knowing how customers will respond to pricing and by which quantity is critical to determine an appropriate use of tariffs for balancing services. The different elasticity cases for each different inverse demand

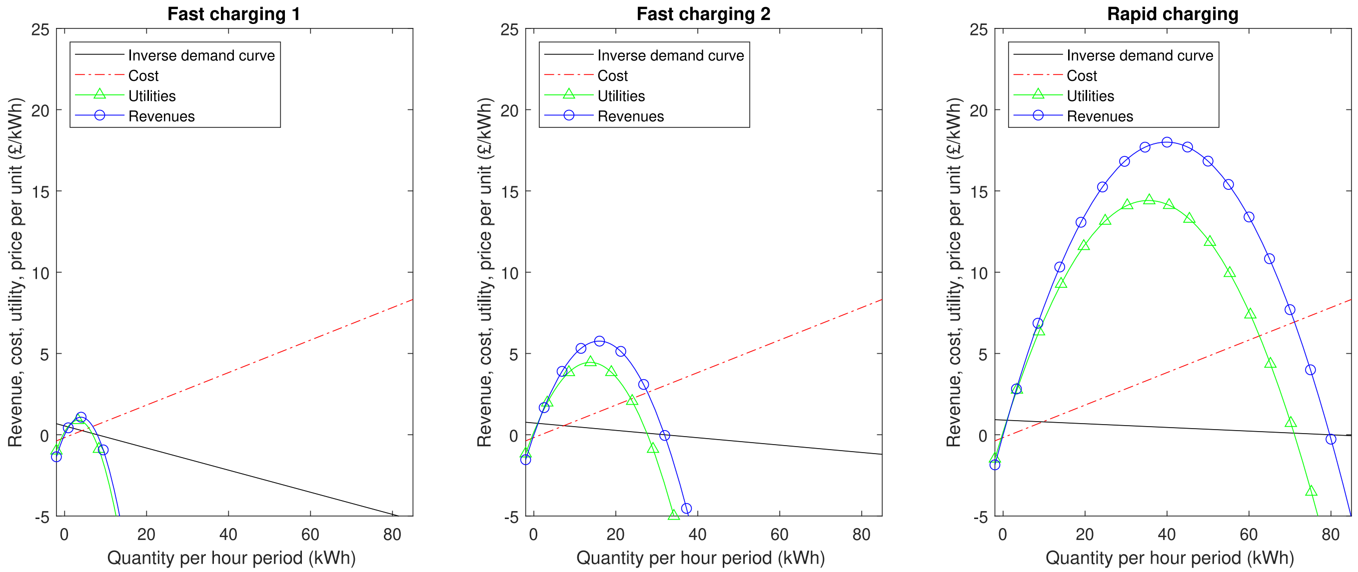

Fig. 4. Inverse demand response, utilities, revenues and costs of EV charging for three different charging ratings.

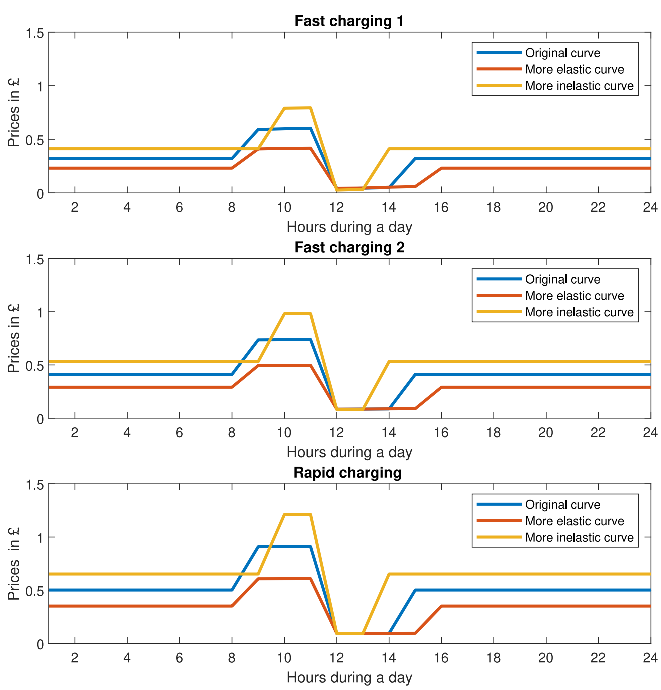

Fig. 5. Dynamic time of use tariffs used to incentivise EVs based on demand inverse curves and charging type cases.

curve could represent when EVs may be subject to substitution effects, for instance when EVs have other options in the area for charging (elastic demand), or when EVs prefer charging from one specific day of the week for personal preference regardless of price (inelastic demand). The results of the dynamic time of use pricing strategy illustrated in Fig. 5 adapt accordingly with varying requirements of demand elasticity, timings for balancing services and charging rating. The prices during balancing services change slightly with cost variation due to available onsite generation of energy per each EV.

3.3. EV response to price

Fig. 6 shows the response from EVs with V2G capability at different charging rates. Fast charging 1 limitations for EV charging shows EVs discharge energy when energy is expensive, this allows EVs to get paid for energy provision to the grid at a high price, a reasonable consideration for battery compensating for degradation when using V2G technology. The charging rate during energy turn down period with fast charging rate 1 is negative and therefore balancing services can be provided from 9:00 h to 11:00 h. However, this changes with fast charging rate 2 because EVs can take more advantage of savings when buying energy at 10:00 h to then discharge power at 11:00 h. Similarly, rapid charging allows EVs to charge at 10:00 h to then discharge at 11 h with a greater energy bid at 9:00 h and 11:00 h compared to fast charging 1 and 2. During energy turn up periods, EVs charge energy taking advantage of the cheap prices. As the charging rate increases EVs charge with the required trip requirements faster. Charging outside balancing services occur in case driver requirements were not met by the end of the turn up period which is the case of fast charging 1 rating. Rapid charging has the biggest bid per hour followed by fast charging 2 and fast charging 1. It is important to point that a smaller charging rate could maintain more average capacity for longer periods of time as it is observed in fast charging 1 and 2 charging rate cases. However, bidding potential occurs for fewer periods of time with higher charging ratings as trip requirements are met at a higher speed.

To continue with the responses results of EV drivers, Fig. 7 illustrates the EV aggregated charging schedule when EVs have unidirectional charging and using an original demand curve for pricing. EV profiles show the majority of EV charging happens when energy is cheaper, which is also when energy turn up provision is needed. However, aggregated biding for every hour is not greater than the V2G option as charging is employed to meet energy requirements without the need to discharge EVs. The charging scheduling is concentrated at 12:00 h as availability at the charging station indicates EVs need to be charged before expected departures. Similar to the V2G case, a greater energy bid is performed with rapid charging, followed by fast charging 2 and 1 respectively. It can also be observed in Fig. 7 that the charging schedule of fast charging 1 and 2 indicate some charging needs to happen outside turn up periods. Thus a greater charging rate is needed to fully take advantage of getting revenue from charging and for participating in balancing services at the same time. When comparing the overall charging schedules from Figs. 6 and 7 we can see that V2G offers greater hourly bidding capacity for both energy turn down and energy turn up. This can be attributed to the possibility to discharge an EV and charge it again when needed at later times as opposed to just charge it to meet trip requirements with unidirectional charging. Thus

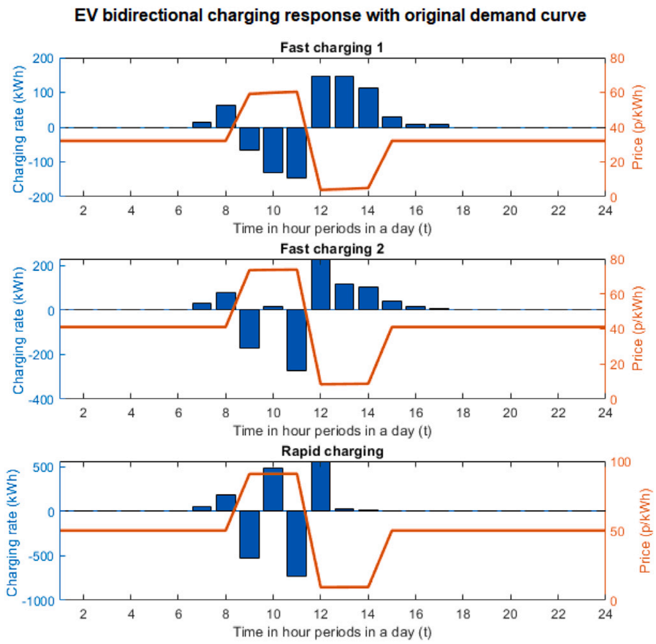

Fig. 6. EV charging profiles as a response to prices with *original demand curve* using different charging type cases and *bidirectional* capability.

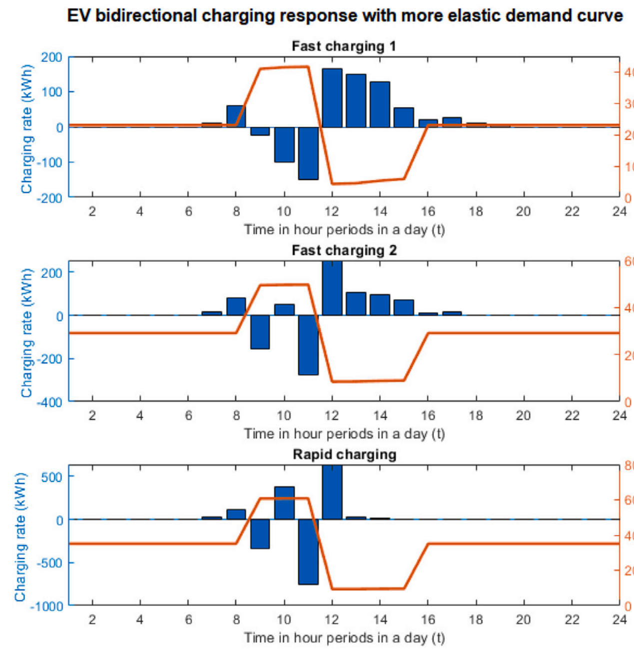

Fig. 8. EV charging profiles as a response to prices with more *elastic demand curve* using different charging type cases and *bidirectional* capability.

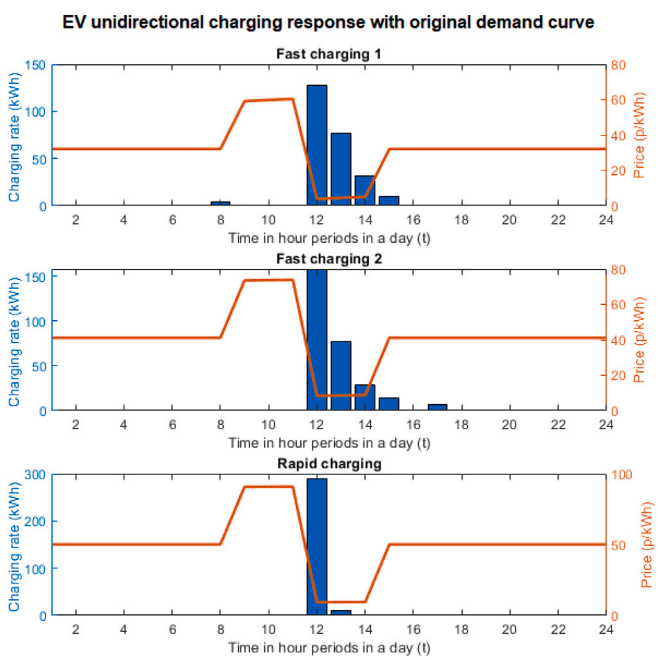

Fig. 7. EV charging profiles as a response to prices with *original demand curve* using different charging type cases and *unidirectional* capability.

energy bid capacity is more limited with unidirectional technology but it is still feasible to have some bidding capacity during turn up period.

Fig. 8 was created with new stochastic EV profiles from an average user type with a more elastic demand curve, the aim of the pricing scheme is to attract more EV users to the charging station, for instance when there is competition or when the charging station aims to influence EV users to charge at a specific day of the week. Fig. 8 shows that overall energy bidding capacity for energy turn up is greater compared to the original demand curve EV profiles as there are more cars which are influenced to arrive at the charging station. However, most periods for energy turn down of Fig. 8 are smaller compared to Fig. 6, this means EVs optimise revenues by taking advantage of the extended turn up periods (cheap energy). Greater bidding capacity is achieved with rapid charging, however for less periods of time compared to fast charging 1 and 2. The energy bids for fast charging 1 and 2 overall have less capacity than the ones with rapid charging but they are still able to provide energy to turn up balancing services from 12:00 h to 15:00 h. The extension of cheap prices during energy turn up periods compared with the original curve results could mean that with the more elastic curve results, EVs have more cost savings, however EV revenues obtained from energy to sell to the charging station should also be considered.

Fig. 9 shows the charging profiles resulted from using a more inelastic EV demand curve with less demand compared to the previous charging figures due to the influence of higher prices on charging station selection. Lower demand at the charging station indicates the timings for energy turn up and energy turn down are shorter. Therefore, Fig. 9 shows more charging happens outside the peak and off peak timings compared to Figs. 6–8 where there are longer periods for balancing services. EVs aim to charge before the energy turn down period if possible to discharge power at high prices when the charging station provides energy turn down services. Compared to previous graphs where EV profiles during energy turn down period were positive with fast charging 2 and rapid charging ratings during one hour, EV profiles in Fig. 9 show negative bidding is feasible for the whole energy turn down period (two consecutive hours). However more positive charging occurs outside energy turn up period as the timings of this period are not sufficient for charging most EVs to meet EV trip requirements. Capacity bidding with the more inelastic demand curve case is less than the capacity bidding in the cases where there are more EVs arriving at the charging station with an original and more elastic EV user type demand curve. The reason for this is fewer EV arrivals and fewer hours for making energy exchange for energy turn up and turn down periods in the more inelastic demand curve case in Fig. 9.

In order to compare the bi-level optimisation model proposed in this paper, a simple fixed tariff of 30 p/kWh is used to compare bidding capacity in Fig. 10. This is the closest comparison to existing research work where a fixed tariff is used to influence driver behaviour to participate in balancing services. It is important to mention that

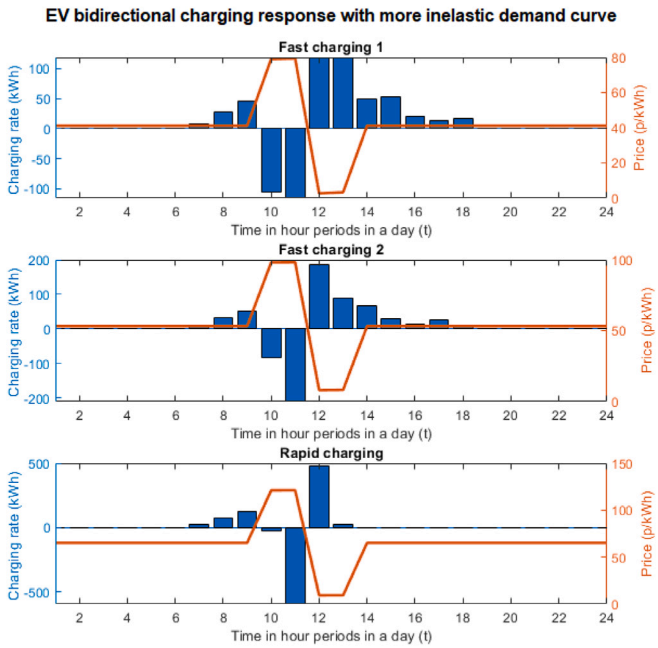

Fig. 9. EV charging profiles as a response to prices with more *inelastic demand curve* using different charging type cases and *bidirectional* capability.

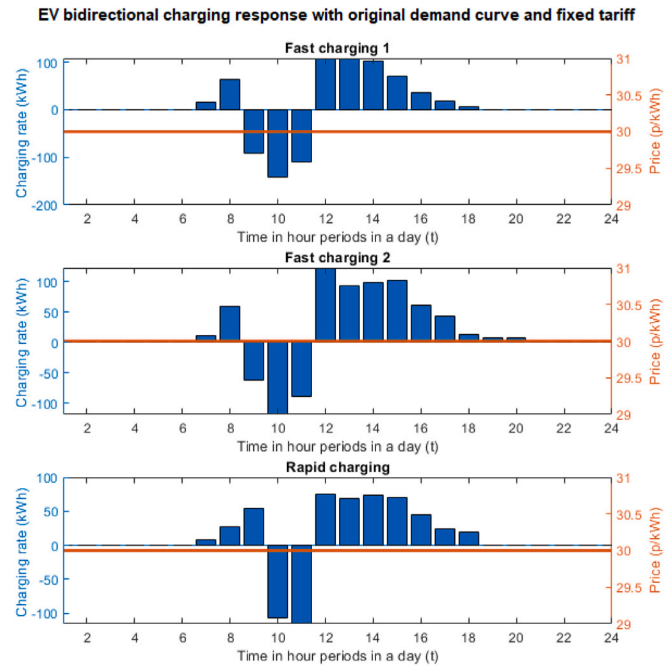

Fig. 10. EV charging profiles as a response to *fixed prices* with *original demand curve* using different charging type cases and *bidirectional* capability.

flexibility has been used to maximise revenues of the charging station and not EVs necessarily, which is not convenient for EV users and the charging station ends up taking advantage of charging and pricing as in the work of Sortomme et al. [29]. The profiles were created using the data inputs from the original demand curve with V2G technology. The results show almost lack of influence over EV charging profiles for energy turn up periods, where charging happens only to meet trip requirements subject to departures. Overall capacity bidding is smaller compared to Fig. 6 as a result of EV users not influenced to discharge and then charge as much energy as possible with a tariff difference. To conclude, it can be observed in Fig. 10 that EV charging has been modelled given a fixed tariff, which does not provide a significant influence over charging of EV users in order to both charge EVs and bid energy into auction balancing service markets.

3.4. Revenues, costs and utilities

Fig. 11 shows percentages of costs and revenues with V2G (bidirectional) technology at different charging ratings, and three inverse demand curves. Revenues come from energy turn down, energy turn up and EV charging, while costs come from energy paid to EVs (energy turn down periods only) and energy purchase from the grid. The biggest revenue from all cases comes from energy turn down followed by EV charging and energy turn up, except for the fast charging 1 with the original demand case where revenue sources from energy turn up are greater than EV charging. The biggest costs for all cases comes from energy paid of EV drivers for V2G provision. Overall cost percentages increase when demand is more elastic and decrease with a more inelastic demand. In contrast, percentage of overall revenues are greatest with the more inelastic demand curve of EVs followed by the original demand curve and then the more elastic curve, except for the rapid charging case where overall revenues are slightly higher in percentage with the more elastic curve than with the more inelastic curve. This difference in percentages of costs and revenues from Fig. 11 can be attributed to pricing strategies at varied demand elasticity and expected demand at the charging station.

Having described costs and revenues in previous paragraphs, total utilities or net profits in Fig. 12 provide values in pounds (£) for a better

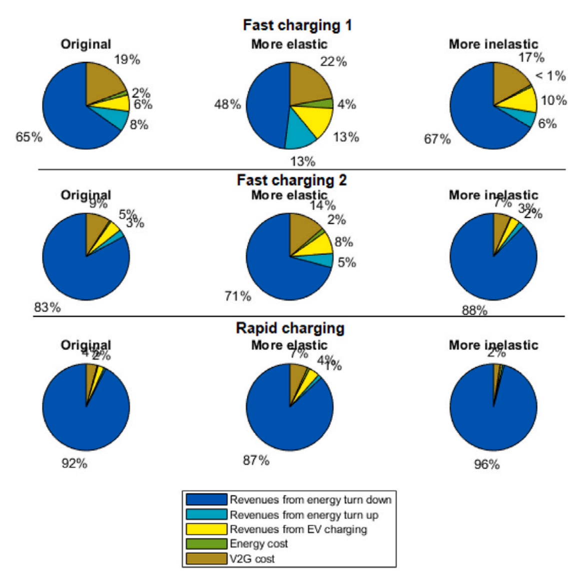

Fig. 11. Potential revenues and costs from different charging type cases with pricing strategies using different inverse demand curves and bidirectional capability.

comparison between all cases. The V2G or bidirectional cases with the more inelastic curve are the most profitable cases, and specifically the case of rapid charging is more profitable than the other charging ratings, this could be a result of the use of increasing prices and overall greater bidding capacity to offer for balancing services compared to the other charging ratings. The V2G case with the original demand curve represents the second place in terms utilities and the case with the more elastic curve is third place. Similar to the V2G cases, G2V or unidirectional cases with greater net profits come from the more inelastic curve for the charging ratings of fast charging 1 and 2, however for the case of rapid charging rating the most profitable case is the original curve. The differences between revenues is more notorious in the V2G cases than in the G2V cases, such differences suggest higher

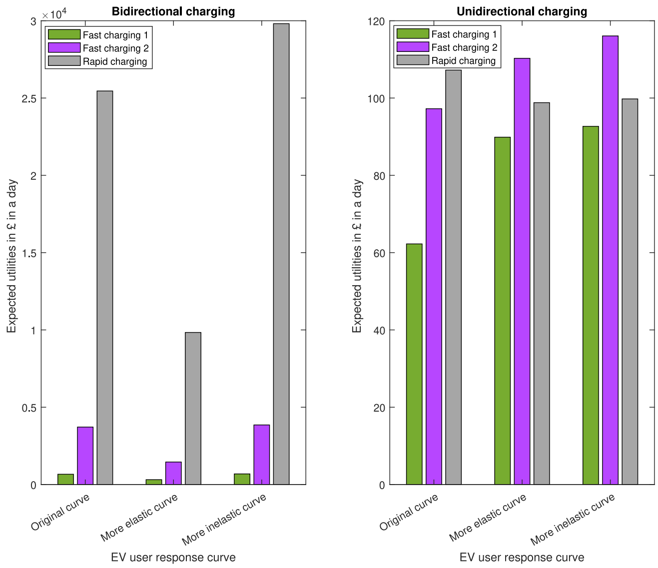

Fig. 12. Net profits with pricing using the three inverse demand curves and charging cases.

prices of energy turn down provide greater revenues. It is assumed however that energy markets for instance balancing services of Grid Operator accept the proposed bidding at the capacity, price and time specified from the EV charging station operator.

4. Conclusions

In this paper, a bi-level optimisation is proposed for pricing and for aggregating energy bidding of a low carbon charging station participating in balancing services. First, pricing strategies are developed for energy bidding to enter in Grid Operator auctions and for generating a desirable charging response from EV drivers. EV charging prices are created to promote charging during energy turn up timings and to promote discharging during energy turn down timings. Second, an EV charging optimisation control strategy is used to determine the charging schedules with bidding quantities during the balancing services periods. Both strategies worked together to announce bids and prices in a day ahead, given historical information to the operation of the charging station e.g., quantity responses to price, PV power forecasting, stochastic variables of EVs (arrivals, departures, trip requirements, state of charge) and charging rate limits from both the charging station and EVs.

The proposed dynamic pricing strategies have demonstrated that EVs can be influenced to provide balancing service provision. Positive revenues are obtained from all cases evaluated, which means the pricing strategies can adequately manage to create economically feasible operations of a low carbon charging station with participation in balancing or ancillary services using different charging technologies. V2G technology has been shown to be the best strategy in terms of bidding capacity. Directions for future research may include consideration of competition impact on revenues, for example EVs can be assumed to know price comparison of several charging stations before arriving. Demand curves could be explored further to create tariffs for different customers with more elastic or more inelastic demand responses.

CRediT authorship contribution statement

Mónica Hernández Cedillo: Conceptualization, Methodology, Software, Investigation, Formal analysis, Data curation, Writing – original draft, Visualization. **Hongjian Sun:** Conceptualization, Formal analysis, Resources, Data curation, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Jing Jiang:** Data curation, Writing – review & editing, Visualization, Project administration. **Yue Cao:** Formal analysis, Advice, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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Appendix. Expanded calculation of Q_t^*

To find an optimal charging demand Q_t^*, we have

$$Q_t^* = arg(r_t' - c_t' = 0).$$

From the derivative of revenues and costs,

$$p_t'(Q_t) \cdot (Q_t) + p_t(Q_t) \cdot (Q_t') - cg_t = 0.$$

Price terms are then substituted,

$$\beta_{1t} \cdot Q_t + \beta_{0t} + \beta_{1t} \cdot Q_t - cg_t = 0.$$

$$\beta_{0t} + 2 \cdot \beta_{1t} \cdot Q_t^* - cg_t = 0.$$

Solving for Q_t, the optimal charging demand quantity is obtained

$$Q_t^* = (cg_t - \beta_{0t})/(2 \cdot \beta_{1t}).$$

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