IET Generation, Transmission & Distribution

Research Article

Optimal operation of aggregated electric vehicle charging stations coupled with energy storage

ISSN 1751-8687
Received on 20th March 2017
Revised 8th June 2017
Accepted on 3rd November 2017
E-First on 19th January 2018
doi: 10.1049/iet-gtd.2017.0134
www.ietdl.org

Mushfiqur R. Sarker[1] ✉, Hrvoje Pandžić[2], Kaiwen Sun[3], Miguel A. Ortega-Vazquez[4]
[1]*Energy Systems Division, Argonne National Laboratory, Lemont, IL, USA*
[2]*Faculty of Electrical Engineering and Computing, University of Zagreb, Zagreb, Croatia*
[3]*Department of Electrical Engineering, University of Washington, Seattle, WA, USA*
[4]*Grid Operations and Planning, Electric Power Research Institute, Palo Alto, CA, USA*
✉ *E-mail: mushfiqsarker@gmail.com*

Abstract: Charging stations are the basic infrastructure for accommodating the energy needs of electric vehicles (EVs). Companies are expected to invest in these charging stations by installing them at locations with a dense concentration of vehicles, such as parking places, commercial centres, and workplaces. In order for investors in EV charging stations to maximise their profits and mitigate the impact on the power grid, these stations would benefit from coupling with an energy storage system (ESS). ESS would be used to arbitrage energy and to balance out the time-variant and uncertain EV energy demand. This study proposes a framework to optimise the offering/bidding strategy of an ensemble of charging stations coupled with ESS in the day-ahead electricity market. The proposed framework accounts for degradation of the ESS, robust scheduling against price uncertainty, as well as stochastic energy demand from EVs. The results show the viability of the proposed framework in providing cost savings to an ensemble of EV charging stations.

1 Introduction

The decarbonisation of the road transport sector is resulting in rapid adoption of electric vehicles (EVs) and is expected to reach 20 million by the year 2020 [1]. EVs use electricity as an energy carrier as opposed to fossil fuels; therefore the successful roll-out of EVs needs to be accompanied by an equally rapid investment in charging infrastructure. The charging infrastructure implies either slower AC or faster DC chargers, whose capacity exceeds 120 kW [2, 3].

EV charging stations (EVCS) are expected to capitalise on natural concentrations of EVs, such as in parking places, commercial centres and work places, among others. These EVCS would have the common objective of serving the uncertain time-variant energy needs at a minimum cost. If aggregated, the EVCS could meet the minimum capacity requirements to participate in day-ahead (DA) electricity markets (e.g. 0.5 MW in CAISO [4] and 0.1 MW in ERCOT [5]). Furthermore, the aggregated energy requirements of several of these EVCS could be better predicted, and an aggregator would be in a better position to participate in DA markets and minimise the electricity procurement costs. To further reduce the costs, the aggregator can perform energy arbitrage with an energy storage system (ESS), which it would manage in conjunction with the ensemble of EVCSs.

The aggregator bidding/offering strategies in the electricity markets have been the focus of several research studies. Such studies include managing an ensemble of individual EVs for market participation, as explored in [6–11]. These works, however, consider charging at residential locations, whereas charging at public locations may provide further benefits. Projects, e.g. [12], indicate with the public (i.e. workplace and/or commercial) EVCS infrastructure in place, 1 in 73 people would opt to drive an EV, as opposed to the national average of 1 in 1400 in the US. Thus, publicly available EVCS are needed to spur the EV penetration and attain projected targets. However, proper methods must be developed in order to manage their operation in an optimal manner.

Several works have studied the operation of public EVCS in power systems, and these may be split into two categories: (i) internal management of EVCS and (ii) external operation and interaction with the power grid. The large majority of the work falls into the first category and include works such as [13–15], among others. In the second category, works exploring the operation and interaction with the power grid include [16–20].

Specifically, in the second category, optimal sizing and operation of an ESS for charging stations are studied in [16] such that energy procurement and ESS operational costs are minimised. A rule-based control algorithm is developed in [17] that routes power between the station, grid, ESS, and photovoltaics. In [18], a scheme is developed that allocates power from the grid plus ESS to a network of charging stations and also routes EV customers. The value of ESS coordination with EVCSs for public buses is explored in [19] while considering the ESS investments and potential cost savings under retail tariffs. Furthermore, an ESS sizing model is developed while considering the stochasticity of the demand [21]. These works [16–19, 21], while managing the external operations, do not consider the cost savings potential of participating in wholesale electricity markets, the uncertainty of EVCS operations, and explicitly the ESS degradation costs which may significantly reduce the revenue potential. On the other hand, the optimal participation of EVCS parking lots in various demand response programs is studied in [20] with consideration of the potential cost savings and EV arrival/departure uncertainty. However, Shafie-khah et al. [20] do not consider the additional benefits an ESS can provide in terms of cost and uncertainty mitigation (e.g. in price arbitrage and EV arrival/departure times). Other related works have studied the impact of degradation on ESS, such as in [22–24]. However, the calculation of the battery degradation cost must be linear to (i) be embedded into a linear optimisation framework, and (ii) be computationally most tractable. The works in [22, 23] do not utilise linear degradation models and also do not study the ESS role for EVCSs.

The EVCSs have not only been considered in theory. Commercial businesses have developed around this concept to take advantage of the growing EV penetration. This sector includes entities that install, e.g. General Electric [25], among others, and those that both install and manage EVCSs, e.g. ChargePoint [26], Tesla Motors [27] among others. For entities that manage EVCSs, their revenue streams are based on the money collected from each EVs charging needs, and for the case of Tesla Motors, their charging network is free to use for their EV models. These entities

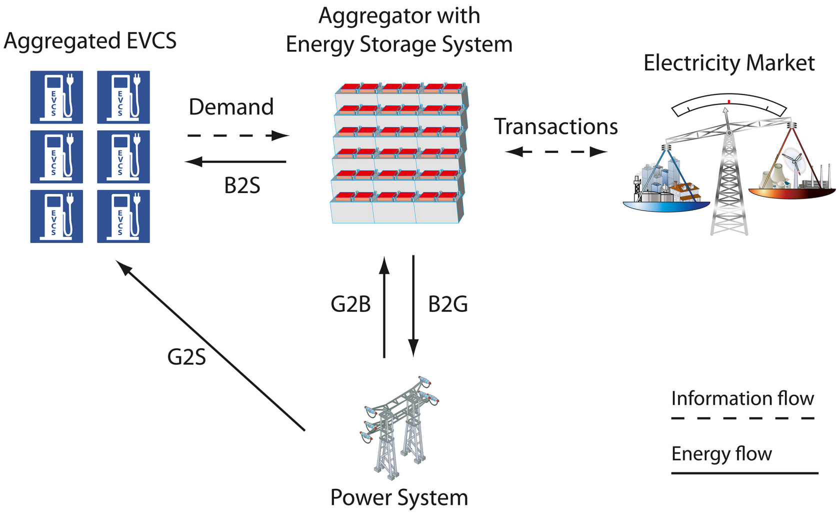

Fig. 1 *Aggregator's interaction with the EVCSs, electricity market, and power system*

would see cost savings if internally aggregating or allowing a third-party aggregator, to manage the energy procurement task for their network of EVCSs.

This paper proposes a framework for an aggregator to manage an ensemble of EVCSs to bid/offer into the wholesale electricity market with the primary goal of minimising operating costs. The aggregator, to further reduce its costs, is equipped with an ESS that acts as a buffer which can provide flexibility to the market bids/offers, while considering the effect of battery degradation due to cycling. The aggregator's DA optimisation model incorporates uncertainty management of market prices, using robust optimisation (RO), and of aggregated EVCS power demand, using stochastic optimisation. For cost-effective operation, the aggregator must effectively manage the uncertainty while considering the trade-off between potential cost reduction compared to the degradation of its ESS. The main contributions of this work are

- Aggregator DA optimisation model managing aggregated power and energy needs of EVCSs based on statistically constructed demand scenarios.
- Uncertainty modelling of the market price using robust optimisation and aggregated EVCS demand using stochastic optimisation.
- Complete ESS model that supplies energy to the grid or to the EVCSs, if economically justifiable, while considering degradation costs.
- The realistic framework of an aggregator exploiting its ESS, power system market, and EVCSs.

The remaining of this paper is organised as follows. Section 2 describes the framework including the perspective of the EVCSs, and interactions between the markets, power grid, EVCSs, and ESS. Section 3 describes the aggregator optimisation model. Section 4 discusses the results and Section 5 concludes the paper.

2 Framework

An aggregator is a profit-seeking business entity who acts as a mediator between the EVCSs and the wholesale electricity market. In order to better manage its demand, this entity may or may not own an ESS; however, in this proposed framework an ESS is considered to exploit its flexibility. The aggregator with the ESS acts as an economic transaction buffer between the EVCS and the grid. Physically within a typical distribution grid, the ESS is connected and located upstream (i.e. nearby the substation transformer) with respect to the connection location of all EVCSs. On the other hand, the aggregator is a virtual entity with only communication channels to and from the EVCS and ESS. It is assumed the distribution grid in which all EVCSs operate can handle the total net load.

Fig. 1 shows the aggregator's interactions with the different entities: an ensemble of EVCSs, power system, and electricity markets. The aggregator coordinates with each EVCS under its management to obtain their expected charging demand requirements for the next day. The expected demand of each EVCS is then used to obtain an expected aggregated demand. The aggregator performs a DA optimisation to schedule its operation at the least-cost while exploiting its ESS capabilities. The ESS charges from the grid in grid-to-battery (G2B) mode when the price of electricity is low. During the periods of high electricity prices, it can either inject electricity back into the grid in battery-to-station (B2S) mode to offset the consumption of the EVCS and thus obtain cost savings, or inject energy back into the grid in battery-to-grid (B2G) mode to obtain additional revenue by selling into the electricity market.

If the aggregator is unable to supply all of the energy needs from the ESS in B2S, it resorts to the power grid in grid-to-station (G2S) mode to obtain the shortage. For such a case where there is a shortage or the aggregator does not own and operate an ESS, it can still provide cost savings by purchasing the bulk power needs of all EVCSs in the wholesale market. The aggregator's optimisation determines the market bids (G2B and G2S services) and offers (B2G services) as a price-taker in the DA wholesale markets.

2.1 EVCS perspective

Each individual EVCS would need to purchase electricity either directly from the wholesale market or via a retailer. However, an EVCS may not meet the minimum energy requirements to participate in the wholesale market, and at the same time, their primary objective is to provide charging services to their EV customers. For these reasons, the role of an aggregator is to manage an ensemble of EVCSs in order to optimise market performance and provide energy services in bulk. Therefore, the aggregator should be reimbursed for its services by the EVCSs. However, the methodology used to charge for its services is not within the scope of this work.

Within this framework, each EVCS is assumed to have in place an internal day-to-day operation for managing each individual EV customer. An interested reader is advised to refer to [13–15] for such methods. In this framework, each EVCS must provide to the aggregator its forecasted demand curve for the following day. Note that internally, each EVCS may accommodate any pricing structure to expense individual EV charging and the resulting forecasted demand would be a by-product of such process. Communication of the demand curve hides proprietary information, for example, the number of EVs arriving at the stations, power requirements of EVs, type of charging protocols used, among others. The major benefit is that an EVCS is not required to change its internal business/operating procedures to conform to the aggregator's framework.

2.2 Eenergy storage system

The ESS, which is owned and operated by the aggregator, is beneficial when scheduling energy at the DA stage. Without the ESS, the aggregator has no other option but to blindly follow the aggregated demand curve. With the ESS at its disposal, however, it can charge and store energy which is either used to offset consumption of EVCSs in B2S mode or sell back into the market in B2G mode. These ESS operations, however, cause battery degradation [28] and therefore the potential cost savings incurred must be higher than the cost of degradation. The ESS is expected to be physically located close to the substation of the distribution feeder. The benefits of this are twofold: (i) only the distribution lines connecting the ESS to the grid need to be revamped in order to allow bi-directional power flow (i.e. providing services in the wholesale markets requires discharging of energy upstream), and (ii) since the distribution grid is of radial structure, discharging to supply EVCSs happens naturally without any changes to the current topology of the grid.

The installation cost of the ESS might be offset by the different streams of revenue that could be collected from its operation. While the primary role of the ESS in this work is to demonstrate its effectiveness to mitigate power peaks that could be generated by simultaneous utilisation of the EVCSs; other sources of income could consider. For instance, in [8], we consider a probabilistic framework in which an aggregated ensemble of EVs' batteries is utilised to participate in energy and reserve markets simultaneously. The proposition value of such approach is high, and similar features could be adopted in the model presented in this study. However, this would go beyond the core idea of the co-locating ESS with FSCs to facilitate the rollout of this type of charging stations.

The following section discusses the mathematical formulation of the optimisation model considering the interactions of the aggregator shown in Fig. 1.

3 Optimisation model

3.1 Aggregator's DA model

In the DA model, the aggregator determines the optimal bidding/offering strategy in the wholesale electricity market. The aggregator determines the amount of energy to sell p_t^{sell} and buy p_t^{buy} from the market to meet the aggregated EVCS demand D_t. The objective function is formulated as follows:

$$\min \quad \Delta t \sum_{t \in \mathcal{T}} \lambda_t \cdot (p_t^{\text{buy}} - p_t^{\text{sell}}) \tag{1a}$$

The buying and selling of energy are priced at the DA market prices λ_t with a timestep of Δt. The objective function (1a) is subject to several constraints. The first set of constraints determines the bidding and offering quantities

$$p_t^{\text{sell}} = p_t^{\text{B2G}} \cdot \eta^{\text{dsg}} \tag{1b}$$

$$p_t^{\text{buy}} = p_t^{\text{G2B}} + p_t^{\text{G2S}} \tag{1c}$$

The aggregator sells energy (p_t^{sell}) by scheduling its ESS to operate in a B2G mode, (p_t^{B2G}) while considering battery discharge efficiency η^{dsg}. On the other hand, the aggregator purchases energy from the market (p_t^{buy}) to both charges the ESS (p_t^{G2B}) and directly supply the power consumption requirements of EVCSs (p_t^{G2S}).

Constraints (1d) and (1e) determine the energy state-of-charge (SoC) of the ESS. In (1d), the SoC is dependent on its previous state, the charging power p_t^{G2B} including the efficiency η^{chg}, the discharging power p_t^{B2G}, and the amount of power discharged from the battery to supply the EVCS, p_t^{B2S}. Constraint (1e) ensures that SoC does not violate its minimum and maximum limits, and at the same time is below its rated capacity BC^{ES}.

$$\text{soc}_t = \text{soc}_{t-1} + \Delta t\big(p_t^{\text{G2B}} \cdot \eta^{\text{chg}} - p_t^{\text{B2G}} - p_t^{\text{B2S}}\big) \quad \forall t \in \mathcal{T} \tag{1d}$$

$$0 \le \underline{\text{SoC}} \le \text{soc}_t \le \overline{\text{SoC}} \le \text{BC}^{\text{ES}} \quad \forall t \in \mathcal{T} \tag{1e}$$

The aggregator obtains forecasts of the power consumption from each EVCS d_t which is then summed to obtain D_t, i.e. $D_t = \sum d_t$. This aggregated demand must be met by a combination of the ESS discharging in B2S mode, p_t^{B2S}, and supplies from the grid in G2S mode, p_t^{G2S}. This is modelled as

$$p_t^{\text{B2S}} \cdot \eta^{\text{dsg}} + p_t^{\text{G2S}} = D_t \quad \forall t \in \mathcal{T} \tag{1f}$$

Constraints (1g) and (1h) ensure that different services provided by the ESS are within its minimum and maximum power limits, $P^{\max}$. These constraints also disallow B2S and B2G to occur simultaneously with G2B, where $x_t \in \{0, 1\}$ is an auxiliary binary variable. For example, if $x_t = 1$, B2S and B2G are allowed whereas G2B is disallowed. This is implemented to ensure the ESS system performs only charging or discharging, and not both simultaneously

$$0 \le p_t^{\text{B2S}} + p_t^{\text{B2G}} \le P^{\max} \cdot x_t \quad \forall t \in \mathcal{T} \tag{1g}$$

$$0 \le p_t^{\text{G2B}} \le P^{\max} \cdot (1 - x_t) \quad \forall t \in \mathcal{T} \tag{1h}$$

Constraint (1i) ensures the total energy in the ESS at the beginning of the optimisation horizon is replenished by the end, i.e. $t = |\mathcal{T}|$.

$$\text{soc}_{t=|\mathcal{T}|} = \text{SoC}^{\text{init}} \tag{1i}$$

Lastly, the non-negativity constraints for G2B, B2G, and B2S powers are considered as

$$p_t^{\text{G2B}} \ge 0, \quad p_t^{\text{B2G}} \ge 0, \quad p_t^{\text{B2S}} \ge 0 \tag{1j}$$

3.2 Demand uncertainty

The aggregator obtains demand requirements of each EVCS for the next operating day, which is then aggregated into D_t. However, each EVCSs demand is prone to uncertainty thus rendering D_t to be uncertain. The main causes are uncertain arrival, departure, and charging times of EVs at EVCSs. Thus, the aggregator must take into consideration the effect of such demand uncertainty on its decision-making process for wholesale market participation. To hedge against this uncertainty, the technique of stochastic optimisation [29] is implemented. This technique takes advantage of the known probability distributions of the uncertain parameters (i.e. D_t). With this, instead of using a single aggregated demand scenario D_t in the optimisation, a set of scenarios $\mathcal{S}$ with index s is considered. In addition, each demand scenario $D_{s,t}$ has expected probability π_s to materialise in the real-time (RT). With this approach, the aggregator obtains the DA bidding/offering schedule that is optimal with respect to all the demand scenarios considering the distribution of uncertainty.

Mathematical formulation of the aggregator's DA stochastic optimisation is as follows:

$$\begin{aligned} \min \quad & \Delta t \sum_{t \in \mathcal{T}} \lambda_t \cdot (p_t^{\text{buy}} - p_t^{\text{sell}}) + \Delta t \sum_{s \in \mathcal{S}} \pi_s \sum_{t \in \mathcal{T}} \lambda_t^{\uparrow} \cdot p_{s,t}^{-} \\ & - \Delta t \sum_{s \in \mathcal{S}} \pi_s \sum_{t \in \mathcal{T}} \lambda_t^{\downarrow} \cdot p_{s,t}^{+} \end{aligned} \tag{2a}$$

s.t.:

$$\text{soc}_{s,t} = \text{soc}_{s,t-1} + \Delta t\big(p_t^{\text{G2B}} \cdot \eta^{\text{chg}} - p_t^{\text{B2G}} - p_{s,t}^{\text{B2S}}\big) \quad \forall s \in \mathcal{S}, t \in \mathcal{T} \tag{2b}$$

$$0 \le \underline{\text{SoC}} \le \text{soc}_{s,t} \le \overline{\text{SoC}} \le \text{BC}^{\text{ES}} \quad \forall s \in \mathcal{S}, t \in \mathcal{T} \tag{2c}$$

$$p_{s,t}^{\mathrm{B2S}} \cdot \eta^{\mathrm{dsg}} + p_t^{\mathrm{G2S}} + p_{s,t}^{-} - p_{s,t}^{+} = D_{s,t} \quad \forall s \in \mathcal{S}, t \in \mathcal{T} \tag{2d}$$

$$0 \le p_{s,t}^{-} \le p_{s,t}^{\mathrm{B2S}} + p_t^{\mathrm{G2S}} \quad \forall s \in \mathcal{S}, t \in \mathcal{T} \tag{2e}$$

$$0 \le p_{s,t}^{+} \le p_{s,t}^{\mathrm{B2S}} + p_t^{\mathrm{G2S}} \quad \forall s \in \mathcal{S}, t \in \mathcal{T} \tag{2f}$$

$$0 \le p_{s,t}^{\mathrm{B2S}} + p_t^{\mathrm{B2G}} \le P^{\max} \cdot x_t \quad \forall s \in \mathcal{S}, t \in \mathcal{T} \tag{2g}$$

$$\mathrm{soc}_{s,t=|T|} = \mathrm{SoC}^{\mathrm{init}} \quad \forall s \in \mathcal{S} \tag{2h}$$

$$p_t^{\mathrm{G2B}} \ge 0, \quad p_t^{\mathrm{B2G}} \ge 0, \quad p_{s,t}^{\mathrm{B2S}} \ge 0 \tag{2i}$$

$$\text{Constraints} \quad (1b), (1c), (1h), (1j) \tag{2j}$$

The objective function (2a) has two additional terms as compared to (1a). The expected cost of purchasing additional energy in the RT market for the scenario s is determined based on the power shortage $p_{s,t}^{-}$ and the buying price $\lambda_t^{\uparrow}$. Similarly, the expected revenue from selling surplus energy in the RT market for the scenario s is determined based on the excess power $p_{s,t}^{+}$ and selling price $\lambda_t^{\downarrow}$. Both of these two terms contain probability π_s representing the chance of the demand scenario s to materialise in the RT.

The objective function is subject to the constraints similar to (1d)–(1i), however, with the addition of stochastic scenario index s. Decision variables that include index s are $\mathrm{soc}_{s,t}$ and $p_{s,t}^{\mathrm{B2S}}$, as they are *wait-and-see* (i.e. recourse) decisions within the stochastic framework [29], and are determined after the demand materialises in the RT [29]. On the other hand, the variables representing G2B (p_t^{G2B}), B2G (p_t^{B2G}), and G2S (p_t^{G2S}) are *here-and-now* decisions, i.e. they have the same value regardless of the scenario. The bidding/offering decisions in the markets, i.e. G2B, B2G, and G2S, are based on the weighted average values over all scenarios. Slack variables $p_{s,t}^{-}, p_{s,t}^{+}$ capture the shortage/excess energy in each scenario. The final energy balance is expected to be obtained from the RT market. On the other hand, B2S does not require interaction with markets and can be controlled by the aggregator as demand materialises in the RT.

3.3 Market price uncertainty

The aggregator, using its ESS, exploits differences in electricity prices λ_t by purchasing energy p_t^{buy} when prices are low, and selling energy p_t^{sell} when prices are high. To participate in the DA market, however, the aggregator forecasts market prices which are uncertain. Such price uncertainties may cause the aggregator to incur monetary losses. For example, with forecasted prices λ_t, the aggregator's optimisation model would schedule and consequently bid into the DA market for large amounts of energy to be procured during the low-price periods. After the DA market clears, however, the realisation of specific prices may be higher than forecasted and thus may leave the aggregator with high monetary losses. To hedge against such uncertainty in the DA, the RO technique is implemented [30]. RO is an uncertainty modelling approach suitable for situations where the range of the uncertainty (e.g. range of electricity prices) is known, while the distribution of uncertainty is unknown.

Deviations of the market prices are modelled within the range $\left[\lambda_t^{\min}, \lambda_t^{\max}\right]$, where $\lambda_t^{\max} = \lambda_t^{\min} + \Delta\lambda_t$ and $\Delta\lambda_t$ is the highest expected price deviation in the period t. To control the level of protection against uncertainty, the parameter Γ is varied from $[0, J]$, where $[J = t \mid \Delta\lambda_t > 0]$. With $\Gamma = 0$, no price deviations are considered and the solution is equivalent to the deterministic case, i.e. no consideration of uncertainty. On the other hand, if $\Gamma = |J|$, the solution is the most conservative since price deviations at all time periods are considered, i.e. prices at all time periods are equal to $\lambda_t^{\max}$. This solution is equivalent to the RO model proposed by Soyster [31]. However, the implemented RO procedure is based on [30] and it allows choosing any Γ from range $[0, J]$, thus fine-tuning the level of conservatism.

The RO-based DA model is formulated as follows:

$$\min \quad \Delta t \sum_{t \in \mathcal{T}} \lambda_t^{\min} \cdot (p_t^{\mathrm{buy}} - p_t^{\mathrm{sell}}) + \Gamma^{\mathrm{RO}} \cdot z^{\mathrm{RO}} + \sum_{t \in \mathcal{T}} y_t^{\mathrm{RO}} \tag{3a}$$

s.t.:

$$\text{Constraints} \quad (1b) - (1j) \tag{3b}$$

$$z^{\mathrm{RO}} + y_t^{\mathrm{RO}} \ge \Delta t \cdot \Delta\lambda_t \cdot \left(p_t^{\mathrm{G2B}} + p_t^{\mathrm{G2S}}\right) \quad \forall t \in \mathcal{T} \tag{3c}$$

$$y_t^{\mathrm{RO}} \ge 0 \quad \forall t \in \mathcal{T} \tag{3d}$$

$$z^{\mathrm{RO}} \ge 0 \tag{3e}$$

In comparison to the deterministic DA objective function (1a), the extended objective function (3a) includes two additional terms containing variables z^{RO} and y_t^{RO} used to account for the known price bounds and parameter Γ. This objective is subject to the original constraints (1b)–(1i) along with constraints (3c)–(3e). Constraint (3c) defines the worst price deviations that could materialise at each time period when interacting with the market in G2B and/or G2S. RO variables z^{RO} and y_t^{RO} are positive, as imposed in constraints (3d) and (3e). This RO model will choose the worst Γ time periods with full price deviation in order to deteriorate the objective function value the most. An interested reader is encouraged to see [30] for details on how to obtain the robust counterpart.

3.4 Battery degradation management

As the battery cells within the ESS charge and discharge, they lose a fraction of their capacity, which is often referred to as battery degradation [28]. The aggregator incurs all costs related to the ESS and thus must consider costs of degradation in its DA optimisation. Degradation management determines the optimal trade-off between revenue collected from services, i.e. B2G and B2S, and the cost of cycling the battery. Without degradation management, the ESS would be exploited to obtain the maximum revenue; however, it would experience excessive degradation that is not economically justified.

Other works have studied the impact of degradation on ESS, such as in [22–24]. However, in this work, we have assumed two degradation characteristics, one of them linear and sensitive only to the energy utilised per cycle, and the other one non-linear and dependent not only on the energy utilised per cycle but also to the depth-of-discharge at the beginning and the end of the cycle. The first model can be easily embedded into the proposed model since it is linear and it does not increase the nature of the mathematical model. The other model is included by means of piecewise linear approximations, which introduce additional binary variables and thus increase the computational burden. Other works propose more elaborate degradation characteristics that could eventually be included in the proposed model [22, 23]. However, such models are mainly non-linear and would not only increase the computational burden but also dilute the main message of the proposed method, which revolves around the utilisation of ESS for optimal operation of EVCS.

The formulation of the aggregator model that considers linear battery degradation characteristic is as follows:

$$\begin{aligned} \min \quad & \Delta t \sum_{t \in \mathcal{T}} \lambda_t \cdot (p_t^{\mathrm{buy}} - p_t^{\mathrm{sell}}) + \\ & \left|\frac{m}{100}\right| \frac{\sum_{t \in \mathcal{T}} soc_t^{\mathrm{deg}}}{\mathrm{BC}^{\mathrm{ES}}} C^{\mathrm{ES}} \cdot \mathrm{BC}^{\mathrm{ES}} \end{aligned} \tag{4a}$$

s.t.:

$$\text{Constraints} \quad (1b) - (1j) \tag{4b}$$

$$\mathrm{soc}_t^{\deg} \geq \mathrm{soc}_{t-1} - \mathrm{soc}_t \quad \forall t \in \mathcal{T} \tag{4c}$$

$$\mathrm{soc}_t^{\deg} \geq 0 \quad \forall t \in \mathcal{T} \tag{4d}$$

The second term in the objective function (4a) represents the degradation costs, where C^{ES} is the price of the ESS (typically in $/kWh), which includes the balance-of-system costs, e.g. battery and labour [32]. In addition, $\mathrm{soc}_t^{\deg}$ determines the amount of energy discharged from the battery in the period t and m is a linear approximation of the battery life as a function of the number of cycles. The parameter m can be estimated based on datasheets of battery manufacturers [33]. The objective function is subject to constraints (1b)–(1i), (4c) and (4d). In (4c), the constraint models $\max\{0, \mathrm{soc}_{t-1} - \mathrm{soc}_t\}$, where the amount of energy discharged from periods $t-1$ to t is determined. It is assumed the same energy discharged was charged into the battery in previous time periods in order to complete one full cycle of degradation [28]. Constraint (4d) imposes non-negativity on $\mathrm{soc}_t^{\deg}$.

The other, more detailed battery degradation model is based on formulation from [28]. This model considers the depth of discharge (DoD), defined as $\mathrm{dod}_t = 1 - \mathrm{soc}_t$. This results in higher degradation effects for the same amount of discharged energy when battery DoD is higher. This model is formulated as follows:

$$\min \quad \Delta t \sum_{t \in \mathcal{T}} \lambda_t \cdot (p_t^{\mathrm{buy}} - p_t^{\mathrm{sell}}) + \sum_{t \in \mathcal{T}} \mathrm{dod}_t^{\deg} \cdot C^{\mathrm{ES}} \cdot \mathrm{BC}^{\mathrm{ES}} \tag{5a}$$

s.t.

$$\text{Constraints} \quad (1\mathrm{b}) - (1\mathrm{j}) \tag{5b}$$

$$\sum_{p \in P} X_t \cdot \omega_{t,p} = \mathrm{dod}_t \quad \forall t \in \mathcal{T} \tag{5c}$$

$$\sum_{p \in P} Y_t \cdot \omega_{t,p} = \rho_t \quad \forall t \in \mathcal{T} \tag{5d}$$

$$\sum_{p \in P} \omega_{t,p} = 1 \quad \forall t \in \mathcal{T} \tag{5e}$$

$$\mathrm{dod}_t^{\deg} \geq \rho_t - \rho_{t-1} \quad \forall t \in \mathcal{T} \tag{5f}$$

$$\begin{bmatrix} \omega_1 \\ \omega_2 \\ \vdots \\ \omega_P \end{bmatrix} \leq [\boldsymbol{M}] \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_{P-1} \end{bmatrix} \tag{5g}$$

$$\sum_{p=1}^{P-1} b_p = 1 \tag{5h}$$

where $\boldsymbol{M}$ is a $p \times (p-1)$ matrix such that $M_{i,j} = 1 \ \forall i = j$ and $i = j+1$, and 0 otherwise.

Objective function (5a) is penalised by the per unit degradation $\mathrm{dod}_t^{\deg}$, multiplied with prices of ESS, C^{ES}, and battery capacity, $\mathrm{BC}^{\mathrm{ES}}$. Constraints (5c) and (5d) are used to relate the current DoD with degradation costs (see Fig. 3 in [28] for reference). X_t and Y_t are points used to construct a piecewise dependency of degradation on DoD with P parts, where X_t is the DoD coordinate and Y_t is the degradation coordinate. Continuous variable $\omega_{t,p}$ is used to identify the piecewise linear segment containing a specific dod_t value, while ρ_t is the degradation variable. Linear interpolation of degradation values on a line segment between two points is enforced in (5e). Actual cost of degradation $\mathrm{dod}_t^{\deg}$ is determined in (5f). Constraints (5g) and (5h) are adjacency constraints to enforce that interpolation is taking place in between the neighbouring points. This model is based on the degradation modelling procedure explained in Section 3.3 of [28], while additional information on how adjacency constraints operate can be found in [34].

3.5 Complete DA model

The complete aggregator's DA model that includes EVCSs demand uncertainty, market price uncertainty, and ESS degradation costs is formulated as follows:

$$\begin{aligned} \min \quad & \Delta t \sum_{t \in \mathcal{T}} \lambda_t \cdot (p_t^{\mathrm{buy}} - p_t^{\mathrm{sell}}) \\ & + \Delta t \sum_{s \in \mathcal{S}} \pi_s \sum_{t \in \mathcal{T}} \lambda_t^{\uparrow} \cdot p_{s,t}^{-} - \Delta t \sum_{s \in \mathcal{S}} \pi_s \sum_{t \in \mathcal{T}} \lambda_t^{\downarrow} \cdot p_{s,t}^{+} \\ & + \Gamma^{\mathrm{RO}} \cdot z^{\mathrm{RO}} + \sum_{t \in \mathcal{T}} y_t^{\mathrm{RO}} \\ & + \left| \frac{m}{100} \right| \frac{\sum_{t \in \mathcal{T}} \mathrm{soc}_t^{\deg}}{\mathrm{BC}^{\mathrm{ES}}} \cdot C^{\mathrm{ES}} \cdot \mathrm{BC}^{\mathrm{ES}} \end{aligned} \tag{6}$$

Objective function (6) is subject to constraints (1b), (1c), (1h), (1i), (2b)–(2i), (3c)–(3e), and (4c) and (4d) or (5c)–(5h). Note that in (4c), (4d) and (5c)–(5h), the stochastic index s is included in SoC and DoD variables, similar to (2b) and (2c).

3.6 RT operation

The presented model is a top-level long-term economic layer that in actual implementation needs to be accompanied by a more detailed control layer. The objective of the control layer is to follow the trajectory passed on by the economic layer. This trajectory is represented by the values of $\mathrm{soc}_{s,t}$ based on the materialisation of the uncertainty. The control layer needs to model physics of the ESS and charging stations more accurately than the economic layer, resulting in increased numerical complexity. Therefore, its look-ahead horizon needs to be much shorter, not more than a couple of hours, while the resolution needs be increased, e.g. 5-min time steps. In case of a faulty forecast used in the economic layer, the control layer might not be able to meet the set-points. In this case, the economic layer would need to re-run with DA market decisions fixed to provide a new trajectory for the rest of the day. This would enable the control layer to continue operating in the feasible area, while the economically inefficient operation caused by the faulty forecast would be reduced. A similar concept where the economic layer lies on top of the control layer to optimise storage operation is proposed in [35]. There are various control layer operating policies that can be used to follow the economic layer trajectory, e.g. [36, 37].

4 Case study

The proposed approach is applied to aggregated EVCS demand D_t obtained by implementing the methodology outlined in [38] using the vehicle data from the National Household Travel Survey (NHTS) [39]. Other EV datasets, e.g. in [40], may also be used. A total of 5000 EVs were tracked over 1000 days to obtain daily charging consumption profiles in the workplace and commercial (e.g. shopping and restaurants) locations equipped with EVCS. The EVCSs are assumed to be fast charging stations using Level 3 charging protocol at 40 kW power rating [3]. Fig. 2 shows the aggregated EVCS charging profiles at workplace (Fig. 2*a*), commercial (Fig. 2*b*), and the sum of these two (Fig. 2*c*). In Figs. 2*a–c*, the light grey area represents the 50% band (i.e. 0.67 of the standard deviation from the mean consumption), the red is the 90% band (i.e. 1.645 of the standard deviation from the mean), and the dark grey is the 100% band, which represents the minimum/maximum of the data. One thousand EVCS charging demand profiles are reduced to a set of scenarios with their respective probabilities π_s using the K-medoids scenario reduction technique [41].

The capacity of the ESS is 1 MWh, however, the available SoC ranges from 15 to 95% of the rated capacity due to constraints on the batteries [42]. Charging and discharging power ratings are 500 kW, while the charging/discharging efficiencies are 95%. The

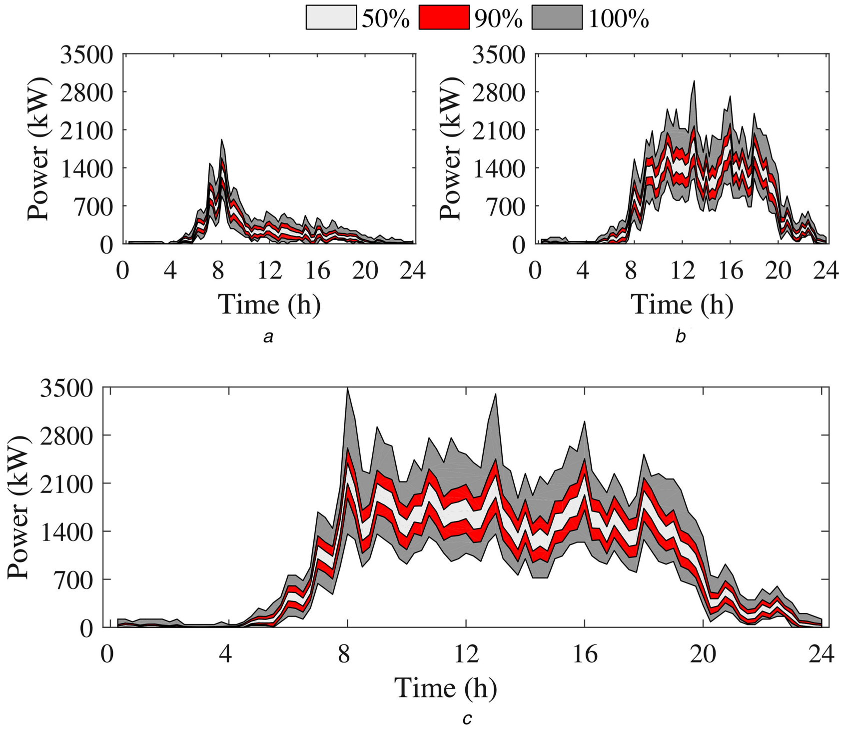

Fig. 2 *DA forecast of aggregated EVCS demand at the*
(a) Workplace location, ***(b)*** Commercial location, and ***(c)*** Sum of the two
Intervals 50, 90, and 100% represent confidence levels that the realisation of EVCS demand lies within the specified bounds

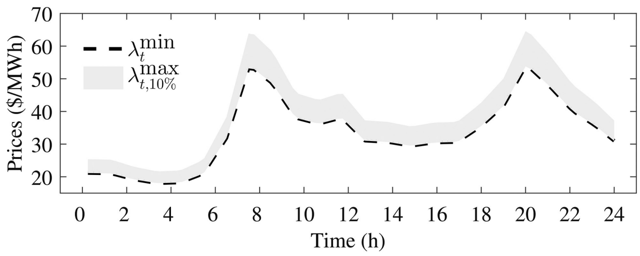

Fig. 3 *DA market price with deviation band for uncertainty*

initial ($t = 0$) SoC of the ESS is randomised. The ESS price is set to 300 $/kWh [43, 44] unless otherwise specified. The linear ESS degradation model is based on lithium iron phosphate batteries ($LiFePO_4$), while the detailed DoD-dependent model is based on NCA batteries.

To represent a typical weekday DA market price, the ERCOT historical data in the period January–March 2016 is used [45]. A typical price curve that best characterises the dataset is obtained using the K-medoids approach [41] and is shown in Fig. 3 as $\lambda_t^{\min}$. The upper bound prices $\lambda_t^{\max}$ used in RO are proportional to $\lambda_t^{\min}$. To discourage scheduling of bids/offer in the RT markets under the stochastic optimisation framework, the buying $\lambda_t^{\uparrow}$ and selling $\lambda_t^{\downarrow}$ prices are assumed to be twice and half the DA typical prices $\lambda_t^{\min}$, respectively.

The proposed approach is a mixed-integer linear program implemented in GAMS 24.2 [46] and solved using IBM CPLEX [47] on an Intel Xeon 3.10-GHz processor with 16 GB of memory. The optimality gap is 0.05%.

4.1 Optimal combination of stochastic scenarios and RO parameters

To minimise its operating cost, the aggregator must determine its optimal bidding/offering strategy in the DA market. To do so, the uncertainty of energy prices and EVCS demand must be estimated using the robustness parameter, Γ, and the number of scenarios $|S|$ in stochastic optimisation, respectively. To determine the best combination of parameters that yield the minimal operating cost, Monte Carlo (MC) simulations are performed [48]. The DA schedules are obtained for all discrete RO parameters in $\Gamma = [0, |T|]$, and stochastic scenarios, $|S| = [1, 5, 10, 25, 50, 100]$. For each combination of $|S|$ and Γ yielding a DA schedule, MC trials are performed to determine the actual cost of operation as the uncertainty materialises. The number of MC trials is set to $\min\{1000, N^{\text{MC}}\}$, where N^{MC} is the number of trials required to obtain a 95% confidence of an error <1% [48]. In the MC simulations, 32 prices and 32 EVCS demand profiles are used totalling 1024 MC trials.

Fig. 4 shows the normalised cumulative distribution function (CDF) of the aggregator operating cost for different combinations of Γ and $|S|$. Cost of each MC trial is normalised over the mean cost of the deterministic MC trials, i.e. $|S| = 1$ and $\Gamma = 0$. In other words, normalisation occurs against cost realisations when uncertainty is not taken into consideration. While all combinations of $|S|$ and Γ are considered, Fig. 4 shows only select combinations for clarity.

From Fig. 4, the CDF curves to the left of the deterministic curve yield the lowest operating cost over all MC trials. In all combinations where $|S| > 1$ and $\Gamma > 0$, the aggregator achieves cost savings. However, if only a single scenario, i.e. $|S| = 1$, is considered with $\Gamma > 0$, specifically the case shown in Fig. 4 where $|S| = 1, \Gamma = 36$, the costs are higher than in the deterministic case. This is caused by the RO, where it increases B2S and decreases B2G energy to protect against unforeseen price deviations that may materialise within the bounds shown in Fig. 3. Thus, it is more favourable to offset the demand needs of the EVCSs using the ESS to discharge in B2S, compared to selling energy back to the grid in B2G mode. Since B2S is highly-favoured with respect to the set with a single scenario, i.e. $|S| = 1$, the operating cost is increased because once the demand materialises, the single demand scenario cannot capture the volatile demand variations thus requiring additional energy purchases.

On the other hand, the cases with $|S| > 1$ and $\Gamma > 0$ outperform the deterministic case. This shows that both the demand and price uncertainty should be properly characterised in order to obtain the minimum operating cost. In addition, from Fig. 4, some combinations outperform others, e.g. $|S| = 10, \Gamma = 72$ and $|S| = 25, \Gamma = 72$. Thus, the price uncertainty parameter $\Gamma = 72$ yields the lowest overall cost, because it balances the DA schedule

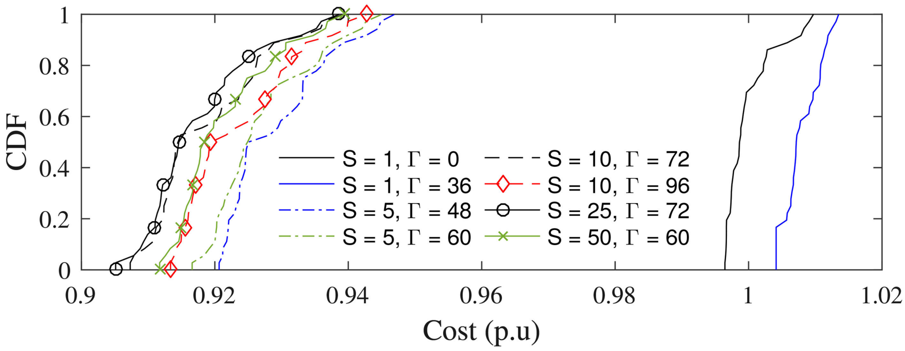

Fig. 4 *Normalised cost CDFs for combinations of stochastic scenarios and price robustness parameter*

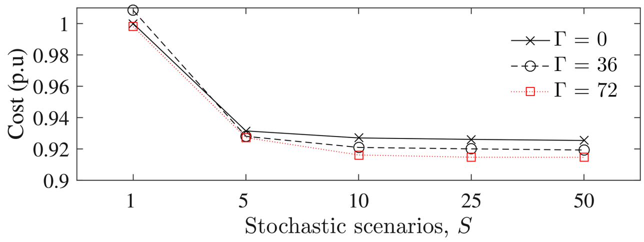

Fig. 5 *Normalised average cost as a function of the number of scenarios*

Table 1 Computational times (seconds)

	Stochastic scenarios, $\|S\|$				
	1	5	10	25	50
$\Gamma = 72$	2.1	9.9	34.3	806	4486

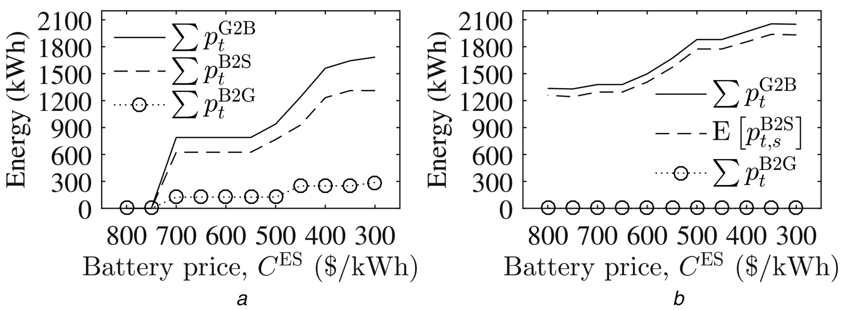

Fig. 6 *Total daily energy scheduled in the deterministic case (a) and with uncertainty management considered (b), as a function of varying ESS prices. Note in (b) the expected value of B2S is shown since it is a function of scenario s*

cost with the RT cost of the realisation of uncertainty. The major difference, however, between these two cases is the number of considered scenarios, i.e. 10 compared to 25 scenarios. In terms of computational burden of stochastic optimisation, as the number of scenarios increases, larger computational times are required to obtain the optimal solution [29]. An interesting feature is the saturation point at which larger number of scenarios does not yield substantial cost savings. This is shown in Fig. 5, where the average normalised costs over all MC trials are shown against the number of stochastic scenarios $|S|$ for different values of Γ. In addition, the computation times for $\Gamma = 72$ over a select number of stochastic scenarios are shown in Table 1. As expected, the average cost experiences a significant decrease from a single scenario to five scenarios. If $\Gamma = 72$, there are clear cost savings between 10 and 25 scenarios (Fig. 4). However, the computational time increases from 34.3 to 806 s. This increase in computational time still keeps the problem tractable for market operations. On the other hand, moving from 25 to 50 scenarios, the cost savings are minimal but the computational time increases drastically to 4486 s.

The combination of the number of scenarios, $|S| = 25$, and the RO parameter, $\Gamma = 72$, yields a balance between the least operating cost over all MC trials and computational burden. This combination is used throughout the remainder of the test case.

4.2 Battery degradation effects

As the ESS is used, it undergoes cycle-life degradation which can be translated into cost, as shown in (4a) and (5a). The ESS price, normalised on a per-kWh basis, is varied from 800 to 300 $/kWh to study the effect on the aggregator's G2B, B2S, and B2G actions. The degradation model, as shown in (4a), is linear and represented by slopes $m = -[0.0017, 0.0006]$. The lower slope is the approximation of the current technology [33], and the higher slope indicates technological life cycle improvement.

The aggregator's daily total energy scheduled as a function of the ESS price is shown in Fig. 6 for G2B, B2S, and B2G services. Fig. 6*a* shows the deterministic case, i.e. $|S| = 1, \Gamma = 0$, whereas Fig. 6*b* considers uncertainty with the best estimates. In both cases, as the ESS price decreases, the amount of energy scheduled for all operating modes monotonically increases because the potential revenue outweighs the degradation costs. As for the specific modes, selling energy back to the grid in B2G mode is unfavourable when uncertainty is considered. For B2G to occur profitably, the aggregator must purchase energy in the low-price periods to charge the ESS (G2B) so it can sell back to the grid by discharging in the high-price periods. However, the uncertainty in market prices renders the arbitrage revenue to be lower than expected and thus as a result, less B2G is scheduled.

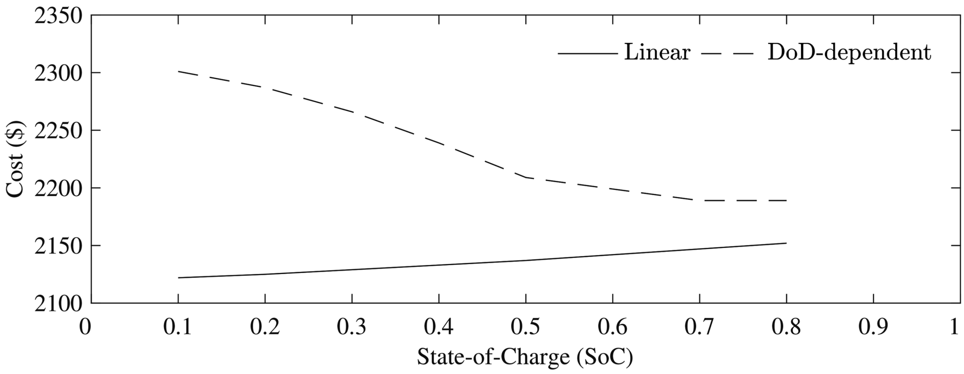

Fig. 7 *Objective function value as function of the initial SoC for linear and DoD-dependent degradation model*

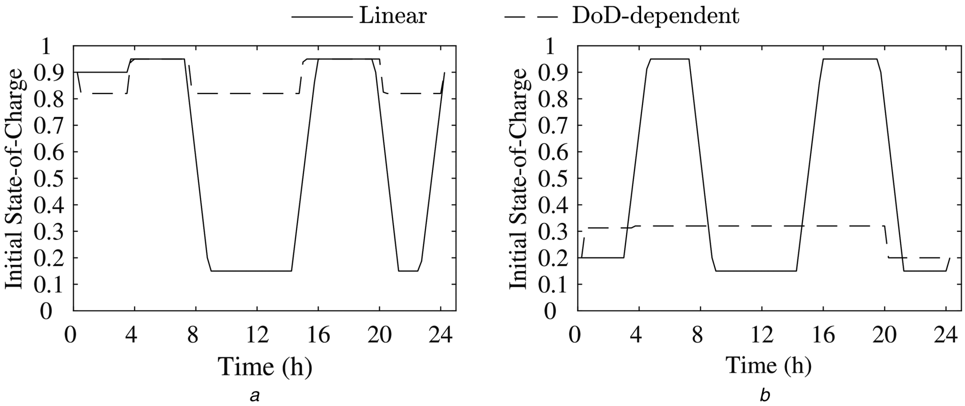

Fig. 8 *SoC throughout the day for linear and DoD-dependent degradation models for* ***(a)*** 90% initial SoC, and ***(b)*** 20% initial SoC

On the other hand, when considering uncertainty management in Fig. 6*b*, the aggregator decreases B2G and increases both G2B and B2S for all battery prices. This happens because, by scheduling B2S, the aggregator offsets the need to purchase energy from the grid (G2S) exactly in periods when the EVCSs require it. Instead, the aggregator uses the energy purchased during low-price periods and stored in the ESS to discharge and offset the EVCS consumption (B2S). The aggregator uses the ESS as a method to reduce economic risks in the electricity markets.

In order to compare the effect that different battery degradation models have on the results, we compare the DoD-dependent degradation model (5a)–(5h) with the basic linear degradation model (4a)–(4d). The DoD-dependent model causes the same degradation effects when discharging the ESS up to 80% SoC as the linear model, and progressively penalises further discharging. Fig. 7 shows the objective function value obtained by models (4a)–(4d) and (5a)–(5h) for different values of initial and final SoCs. Due to lower penalisation of ESS discharging, the linear model results in lower objective function values. Since the DoD-dependent model aggressively penalises deep discharges, the initial SoC has a significant role in its objective function value, favouring high initial SoC. This is further elaborated in Fig. 8, which shows ESS SoC for (Fig. 8*a*) 90% and (Fig. 8*b*) 20% values of the initial SoC. When starting the day at high SoC, the linear model tends to perform deep discharges of the ESS, while the DoD-dependent model keeps the SoC at high levels not to incur high degradation costs. The DoD-dependent model performs two full cycles, but these cycles are much shallower than in the linear model. Similarly, when starting the day at low SoC, the linear model performs two full charging/discharging cycles, while the DoD-dependent model keeps the SoC at low levels, as otherwise, it would incur high degradation cost when discharging the ESS.

4.3 DA schedules

The aggregator determines its bidding/offering schedule in the DA as shown in Fig. 9 for the deterministic case, and in Fig. 10 for the case considering uncertainty with the best uncertainty parameter estimates. The net energy purchases p_t^{buy} with and without the ESS, the power sold p_t^{sell}, and DA market prices are shown in the figures. The net purchases with the ESS are equivalent to $p_t^{\text{buy}} = p_t^{\text{G2S}} + p_t^{\text{G2B}} - \mathrm{E}\big[p_{t,s}^{\text{B2S}}\big]$, whereas without the ESS it is equivalent to $p_t^{\text{buy}} = p_t^{\text{G2S}}$. Also, $p_t^{\text{sell}} = p_t^{\text{B2G}}$ in both cases. If in any period, the p_t^{buy} with ESS is greater than p_t^{buy} without ESS, then the ESS is performing in G2B and thus additional purchases are made. On the other hand, if the opposite is true (less than), then B2S is occurring which reduces purchases in the market (i.e. offsets G2S).

In the deterministic case ($|S| = 1, \Gamma = 0$), the aggregator exploits the low-price periods (0300–0430, and 1415–1545 h) by scheduling purchases in the form of G2B (p_t^{buy} with ESS in red is larger in these periods). During the high-price periods (0715–0845, and 1930–2100 h), the aggregator discharges the ESS to obtain revenue from the market (p_t^{buy} with ESS in red is lower in these periods). The discharging, however, is split between B2G (p_t^{sell}) with 526.3 kWh and B2S with 1074 kWh total. The total B2S energy is greater than B2G because of the demand needs of the EVCS, as shown in Fig. 2*c*, correlate with the high-price regions. Thus, it is economical to discharge, while incurring degradation costs, to offset the EVCSs consumption in B2S and thus consequently reduce purchases directly from the market in G2S. Furthermore, B2G is only exploited when the potential revenue that can be obtained by selling in the market outweighs both the degradation cost and the potential benefit of performing in the B2S mode to offset G2S. This effect can be seen in Fig. 9 where B2G (p_t^{sell}) is scheduled to be sold during the high-price periods but not during the peaks because it is more economical to perform B2S due to correlation with EVCS demand.

In Fig. 10, the DA schedule is shown considering the best estimates of uncertainty management, i.e. $|S| = 25, \Gamma = 72$. As compared to the deterministic case, G2B is spanned across more time periods (i.e. p_t^{buy} with ESS is larger). This occurs because the RO approach makes the aggregator hedge against the worst case of

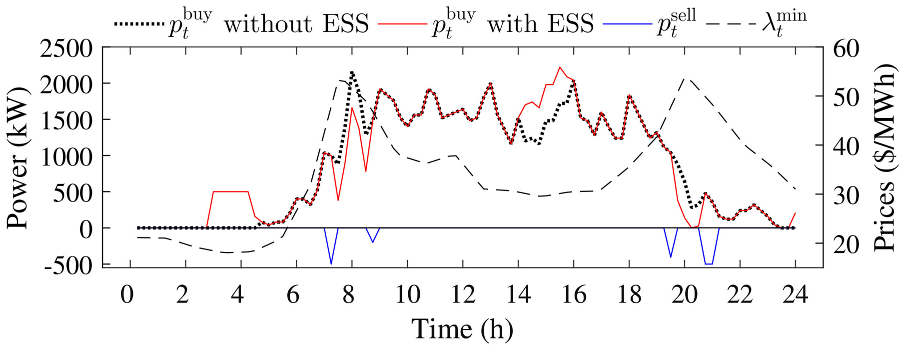

Fig. 9 *DA market buying and selling strategy in the deterministic case*

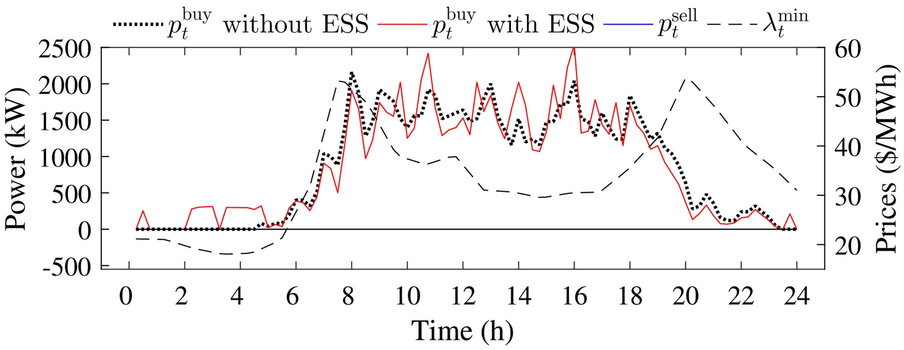

Fig. 10 *DA market buying and selling strategy when uncertainty management is considered. Note that the expected value of B2S is used in p_t^{buy} with ESS since it is dependent on the scenario set*

Table 2 Yearly cost/benefit analysis

	Costs, $			Benefit, $	Total, $
	G2S	G2B	ES deg.	B2S/B2G	
(1) DAM	311,092	—	—	—	311,092
(2) DAM + ESS	263,771	27,185	3627	47,321	247,262

an unforeseen increase in market prices. As an example, in Fig. 9, the lowest-price period is 0315 h, and the maximum power of 500 kW is scheduled by the aggregator. However, potential uncertainty exists in the estimate of the market price, and thus the aggregator is risk-averse by scheduling 212 kW in that time period as shown in Fig. 10.

When considering uncertainty (Fig. 10), the aggregator does not schedule any B2G ($p_t^{sell} = 0$ in all periods). Instead, it increases the average B2S to 2161 kWh compared to the 1074 kWh in the deterministic case in Fig. 9. An example of this can be seen from periods 1800 to 2330 h, where B2S is performed consistently (p_t^{buy} with ESS is lower). This occurs because in the worst case the market prices may be higher than expected, and thus there might be an adverse effect on the overall cost caused by excessive purchasing in G2S mode from the market. In addition, since the aggregator also considers multiple scenarios of demand that may materialise, the B2S is scheduled as an average response across all scenarios, as opposed to only a single scenario. Therefore, B2S is not only increased significantly but also spread across multiple time periods that correlate with the EVCS demand (see Fig. 2*c*) to offset G2S purchases.

4.4 Yearly cost/benefit analysis

The aggregator must obtain a monetary benefit when participating in the electricity markets and scheduling the ESS. A yearly cost/benefit analysis is performed in two cases: (1) DA market (DAM) case where the aggregator schedules the aggregated EVCSs without the ESS, and (2) DAM including the ESS. The results are summarised in Table 2.

In case 1, the aggregator manages the EVCSs and participates in the DAM, which incurs a cost of $311,092 which is solely based on purchases from the market in G2S mode. Furthermore, if the aggregator uses an ESS in conjunction with the market schedule, it obtains revenue benefits of $47,321 by performing in B2S/B2G mode. However, this introduces additional costs related to purchasing energy in the markets in G2B mode and the respective degradation costs when charging/discharging as shown in Table 2. It can be seen with the inclusion of an ESS, the G2S costs are reduced from $311,029 to $263,771 because now the ESS can perform G2B to store energy during low-price periods instead of resorting to full G2S participation. By implementing an ESS, the total costs are reduced from the DAM case by 20.5%. To calculate the simple return on investment (ROI) of the ESS, the total cost savings after its implementing are compared to its capital cost investment. If the 1 MWh ESS investment is $300,000 ($300/kWh), the yearly ROI is 21.3%, which means the investment will be paid off in 4.7 years. More detailed ESS investment models are available in [49, 50].

Furthermore, the ESS can generate further revenue from other markets, e.g. ancillary services, if dual participation is considered. The interested reader is encouraged to refer to [8] for further details on dual participation strategies. Therefore, the presented comparison of yearly revenue should be used as a basis for a detailed cost/benefit analysis.

5 Conclusion

This paper presents a framework for an aggregator to manage an ensemble of EV charging stations to participate in the DA electricity markets while striving to minimise energy procurement costs. To enable a further stream of benefits, the aggregator operates its ESS to charge during the low-price periods in G2B mode, and then to discharge to the grid to offset the stations' consumption in B2S mode or to inject power to the grid directly in B2G mode. However, since the charging/discharging of the ESS causes degradation, this effect is translated into an economic operating cost and explicitly taken into consideration. To manage uncertainty, a stochastic and robust optimisation approaches are combined with the charging station power needs and market prices, respectively. The utilisation of robust optimisation for market price uncertainty allows fine-tuning the conservativeness of the solution by varying the parameter Γ. On the other hand, weighed stochastic scenarios capture the expected cost of operations over demand scenarios that are estimated probabilistically. The benefits of this framework are twofold. First, the volatile and high-power needs of the charging stations are now procured in the DA market, and second, the stations can now focus on their primary role to provide services to EV customers as opposed to attempting to reduce energy procurement costs.

Results show that the aggregator provides extensive benefits to the charging stations by managing their energy procurement from the wholesale market. The cost savings, however, are only experienced if uncertainty is properly hedged against. The total cost savings could be significant if both DA market participation and uncertainty management are implemented with an ESS, as opposed to a case in which an ESS is not available.

As for the tradeoff in cycling the ESS compared to the incurred costs, B2S is preferred over B2G because B2S directly offsets purchasing energy from the market to supply the stations. However, such services are a function of the ESS price. At high ESS prices, charging/discharging is decreased since the degradation is too high to justify the potential revenue from market arbitrage.

6 Acknowledgments

This work was supported in part by the National Science Foundation under grant number 1239408, and in part by the Croatian Science Foundation under project IP-2014-09-3517.

7 References

[1] 'Global EV outlook: understanding the electric vehicle landscape to 2020'. Report, International Energy Agency, 2013
[2] Scholer, R., McGlynn, H.: 'Smart charging standards for plug-in electric vehicles'. SAE Technical Paper 2014-01-1823, 2014
[3] 'Plug-in electric vehicle handbook for public charging station hosts'. Report, U.S. Department of Energy: Energy Efficiency & Renewable Energy, 2012
[4] 'Demand response frequently asked questions – CAISO', 2016. Available at goo.gl/vdmpE3
[5] 'Load participation in the ercot nodal market'. Report, ERCOT, 2016
[6] Vayá, M.G., Andersson, G.: 'Optimal bidding strategy of a plug-in electric vehicle aggregator in day-ahead electricity markets under uncertainty', *IEEE Trans. Power Syst.*, 2015, **30**, (5), pp. 2375–2385
[7] Sarker, M.R., Ortega-Vazquez, M.A., Kirschen, D.S.: 'Optimal coordination and scheduling of demand response via monetary incentives', *IEEE Trans. Smart Grid*, 2015, **6**, (3), pp. 1341–1352
[8] Sarker, M., Dvorkin, Y., Ortega-Vazquez, M.: 'Optimal participation of an electric vehicle aggregator in day-ahead energy and reserve markets', *IEEE Trans. Power Syst.*, 2015, **PP**, (99), pp. 1–10
[9] Ortega-Vazquez, M.A., Bouffard, F., Silva, V.: 'Electric vehicle aggregator/system operator coordination for charging scheduling and services procurement', *IEEE Trans. Power Syst.*, 2013, **2**, (2), pp. 1806–1815
[10] Calvillo, C., Sánchez-Miralles, A., Villar, J., *et al.*: 'Optimal planning and operation of aggregated distributed energy resources with market participation', *Appl. Energy*, 2016, **182**, pp. 340–357. Available at http://www.sciencedirect.com/science/article/pii/S030626191631217X
[11] Shafie-khah, M., Heydarian-Forushani, E., Golshan, M., *et al.*: 'Optimal trading of plug-in electric vehicle aggregation agents in a market environment for sustainability', *Appl. Energy*, 2016, **162**, pp. 601–612
[12] 'Ev everywhere: workplace charging challenge progress update 2014'. Report, U.S. Department of Energy: Energy Efficiency & Renewable Energy, 2014
[13] Fan, P., Sainbayar, B., Ren, S.: 'Operation analysis of fast charging stations with energy demand control of electric vehicles', *IEEE Trans. Smart Grid*, 2015, **6**, (4), pp. 1819–1826
[14] You, P., Yang, Z., Chow, M.Y., *et al.*: 'Optimal cooperative charging strategy for a smart charging station of electric vehicles', *IEEE Trans. Power Syst.*, 2016, **31**, (4), pp. 2946–2956
[15] Hafez, O., Bhattacharya, K.: 'Integrating ev charging stations as smart loads for demand response provisions in distribution systems', *IEEE Trans. Smart Grid*, 2016, **PP**, (99), pp. 1–1
[16] Negarestani, S., Fotuhi-Firuzabad, M., Rastegar, M., *et al.*: 'Optimal sizing of storage system in a fast charging station for plug-in hybrid electric vehicles', *IEEE Trans. Transp. Electrification*, 2016, **PP**, (99), pp. 1–1
[17] Machiels, N., Leemput, N., Geth, F., *et al.*: 'Design criteria for electric vehicle fast charge infrastructure based on Flemish mobility behavior', *IEEE Trans. Smart Grid*, 2014, **5**, (1), pp. 320–327
[18] Bayram, I.S., Michailidis, G., Devetsikiotis, M., *et al.*: 'Electric power allocation in a network of fast charging stations', *IEEE J. Sel. Areas Commun.*, 2013, **31**, (7), pp. 1235–1246
[19] Ding, H., Hu, Z., Song, Y.: 'Value of the energy storage system in an electric bus fast charging station', *Appl. Energy*, 2015, **157**, pp. 630–639
[20] Shafie-khah, M., Heydarian-Forushani, E., Osório, G.J., *et al.*: 'Optimal behavior of electric vehicle parking lots as demand response aggregation agents', *IEEE Trans. Smart Grid*, 2016, **7**, (6), pp. 2654–2665
[21] Bayram, I.S., Abdallah, M., Tajer, A., *et al.*: 'A stochastic sizing approach for sharing-based energy storage applications', *IEEE Trans. Smart Grid*, 2017, **8**, (3), pp. 1075–1084
[22] Ma, Z., Zou, S., Liu, X.: 'A distributed charging coordination for large-scale plug-in electric vehicles considering battery degradation cost', *IEEE Trans. Control Syst. Technol.*, 2015, **23**, (5), pp. 2044–2052
[23] Hoke, A., Brissette, A., Smith, K., *et al.*: 'Accounting for lithiumion battery degradation in electric vehicle charging optimization', *IEEE J. Emerg. Sel. Top. Power Electron.*, 2014, **2**, (3), pp. 691–700
[24] 'A practical battery wear model for electric vehicle charging applications', *Appl. Energy*, 2014, **113**, pp. 1100–1108
[25] 'General electric – electric vehicle charging stations'. Available at http://www.geindustrial.com/products/electric-vehicle-charging-stations
[26] 'Chargepoint'. Available at http://www.chargepoint.com
[27] 'Tesla motors supercharger stations'. Available at http://www.teslamotors.com/supercharger
[28] Ortega-Vazquez, M.A.: 'Optimal scheduling of electric vehicle charging and vehicle-to-grid services at household level including battery degradation and price uncertainty', *IET Gener. Transm. Distrib.*, 2014, **8**, (6), pp. 1007–1016
[29] Conejo, A.J., Carrión, M., Morales, J.M.: '*Decision making under uncertainty in electricity markets*', vol. **1** (Springer, New York, 2010)
[30] Bertsimas, D., Sim, M.: 'The price of robustness', *Oper. Res.*, 2004, **52**, (1), pp. 35–53
[31] Soyster, A.L.: 'Convex programming with set-inclusive constraints and applications to inexact linear programming', *Oper. Res.*, 1973, **21**, (5), pp. 1154–1157
[32] Carnegie, R., Gotham, D., Nderitu, D., *et al.*: 'Utility scale energy storage systems: benefits, applications, and technologies'. Report, State Utility Forecasting Group, 2013
[33] 'Amp20 lithium ion prismatic cell'. Available at http://www.a123systems.com/prismatic-cell-amp20.htm
[34] Guéret, C., Marc, S., Prins, C.: '*Applications of optimization with Xpress-MP*', vol. **1** (Dash Optimization Ltd., Genova, 2005)
[35] Almassalkhi, M., Dvorkin, Y., Marley, J., *et al.*: 'Incorporating storage as a flexible transmission asset in power system operation procedure'. 2016 Power Systems Computation Conf. (PSCC), June 2016, pp. 1–7
[36] Koutsopoulos, I., Hatzi, V., Tassiulas, L.: 'Optimal energy storage control policies for the smart power grid'. 2011 IEEE Int. Conf. Smart Grid Communications (SmartGridComm), October 2011, pp. 475–480
[37] Marley, J.F., Hiskens, I.A.: 'Multi-period ac-qp optimal power flow including storage'. 2016 Power Systems Computation Conf. (PSCC), June 2016, pp. 1–7
[38] Sun, K., Sarker, M., Ortega-Vazquez, M.: 'Statistical characterization of electric vehicle charging in different locations of the grid'. 2015 IEEE Power Energy Society General Meeting, July 2015, pp. 1–5
[39] 'National household travel survey (nhts) data'. Report, NHTS, 2009. Available at www.nhts.ornl.gov
[40] Bayram, I.S., Zamani, V., Hanna, R., *et al.*: 'On the evaluation of plug-in electric vehicle data of a campus charging network'. 2016 IEEE Int. Energy Conf. (ENERGYCON), April 2016, pp. 1–6
[41] Kaufman, L., Rousseeuw, P.J.: '*Clustering by means of medoids*', Delft University of Technology: reports of the Faculty of Technical Mathematics and Informatics (Faculty of Mathematics and Informatics Delft, The Netherlands, 1987)
[42] Doughty, D.H., Pesaran, A.: 'Vehicle battery safety roadmap guidance'. Report, National Renewable Energy Laboratory, 2012
[43] 'Levelized cost of energy storage analysis'. Report, Lazard, 2015. Available at http://www.lazard.com/media/2391/lazards-levelized-cost-of-storage-analysis-10.pdf
[44] D'Aprile, P., Newman, J., Pinner, D.: 'The new economics of energy storage'. Available at http://www.mckinsey.com/business-functions/sustainabilityand-resource-productivity/our-insights/the-new-economics-of-energy-storage
[45] 'Ercot day-ahead market'. Available at www.ercot.com/mktinfo/dam
[46] 'Gams – a user's guide'. Available at www.gams.com/dd/docs/bigdocs/GAMSUsersGuide.pdf
[47] 'User's manual for cplex'. Report, IBM, 2009
[48] Hahn, G.J., Shapiro, S.S.: '*Statistical models in engineering*' (Wiley, New York, 1967)
[49] Mateo, C., Reneses, J., Rodriguez-Calvo, A., *et al.* 'Cost-benefit analysis of battery storage in medium-voltage distribution networks', *IET Gener. Transm. Distrib.*, 2016, **10**, (3), pp. 815–821
[50] Dvorkin, Y., Fernández-Blanco, R., Kirschen, D.S., *et al.*: 'Ensuring profitability of energy storage', *IEEE Trans. Power Syst.*, 2017, **32**, (1), pp. 611–623