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A Planning Model for Electric Vehicle Aggregators Providing Ancillary Services

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ABSTRACT This paper introduces a planning model that can be used by an investor who would like to provide ancillary services (AS) to electricity markets. The proposed model helps the investor evaluate two potential options: aggregating distributed batteries in electric vehicles (EVs) or using a dedicated energy storage system (ESS). For EV aggregations in AS markets, the targeted EV fleet size, which is a function of energy tariff charged by the EV aggregator, is a key planning consideration. In the case of ESS, the physical size is the main planning consideration. Using the proposed model, the two options for maximizing the investor's long-term payoffs are analyzed and compared by assuming the same initial investment cost for both options. Accordingly, the investor's daily bidding strategy in AS markets is optimized for each case. The net present worth is used as the basis for comparing the two investment options, and sensitivity analyses are carried out to study the impact of planning and operation variables on the feasibility of the two options. Simulation results consider both options and discuss the results for providing AS to electricity markets.

INDEX TERMS Power system planning, EV aggregators, energy storage systems, V2G, electricity market

NOMENCLATURE

A. INDICES

it, d, w, y	Indices for EV, hour, day, week and year numbers
p	Index for trip number

B. PARAMETERS AND CONSTANTS

$\alpha^D, \alpha^U, \alpha^R, \alpha^{RAD}, \alpha^{RAU}$	Estimated regulation down, regulation up, responsive reserve, ramp down, ramp up commands (as % of bid capacities).
δ	Compensation factor for unplanned departures.
η	Battery charging/discharging efficiency
φ and Φ	Minimum and maximum permissible SOC limits (as % of MC)
π	Probability that a random EV departs
π^A	Accumulated probability of random departure
σ^E	Forecasted energy price (\$/kWh).
$\sigma^D, \sigma^U, \sigma^R, \sigma^{RAD}, \sigma^{RAU}$	Forecasted price of regulation down, regulation up, responsive reserve, ramp down and ramp up (\$/kWh).
τ^p	Trip time for p-th scheduled trip
v	EV availability; 1 if EV is available, 0 otherwise
ω	Expected % of EVs remaining to perform V2G
r	Discount rate
E	Energy needed for scheduled trip at $t = \tau^p$ (kWh)
K_w	Weighting factor of week w
$BatC$	Battery replacement cost (\$/kWh)
BiC	Retrofit cost to support bidirectional $V2G$ (\$/kW)
ChC	Battery charger cost (\$/kW)
$ComC$	Communications cost for each EV (\$)
EnC	Battery energy capacity cost (\$/kWh)
SC	Smart meter cost for each EV (\$)

NP	Total number of scheduled trips per day
T	Time span in operation day (hours).
NY, NW	Number of years and number of weeks
NT	Total available EVs in the targeted region
NA	Number of participating EVs in aggregation
NEV	Number of EV usage profiles
MC_{Max}	Maximum energy rating (kWh)
MP_{Max}	Maximum power rating (kW)

C. VARIABLES

β	Energy tariff charged to the customer ($/kWh)
γ	Percentage of EVs participating in aggregation
DC	Discharging cost ($/kWh)
SOC	Estimated state of charge (kWh)
POP	Preferred operating point (kW)
AP^D, AP^U	Power capacity available for regulation down,
AP^R	regulation up, reserves, ramp down, and ramp up (kW).
AP^{RAD}, AP^{RAU}	(kW).
$E[\cdot]$	Expected value
MP, MC	Maximum power (kW) and energy ratings (kWh)
$R^D R^U, R^R R^{RAD}, R^{RAU}$	EVA's capacity bid of regulation down, regulation up, responsive reserve, ramp down, and ramp up (kW).
FP	Final power draw (kW)
FP^-	A conservative estimation of the final power draw
TP	Project's total payoff ($)
OpP	Annual operation payoff ($)
$InvC$	investment cost ($)
OpI, OpC	Expected daily operational income and cost to EVA
g	Battery depreciation cost paid by EVA to EV owners

I. INTRODUCTION

THE last few years have witnessed a dramatic rise in the adoption of electric vehicles (EVs). A major reason for this rise is customer' desire to reduce the emission of hazardous gasses and air pollution that affect the environment [1]. It has been reported that CO2 emissions drop by 2.2 tons/year for each conventional car being replaced by an EV [2]. Reducing dependency on fossil fuels is another driver of this trend, especially since it is estimated that the usage of plug-in hybrid electric vehicles (PHEVs) may reduce the global consumption of gasoline by 6.5 million barrels a day [3].

EVs can also be charged using energy produced by renewable energy sources, which further reduces their environmental impact as the penetration of renewable energy grows in the future [3]. Several examples of the increasing penetration of EVs can be observed around the world. In China for example, it is projected that 200 million EVs will be on the road by 2050 [4]. In Norway, the percentage of EVs and PHEVs that were sold in 2015 was over 20% of all passenger cars sold that year [5]. However, EVs have some disadvantages, such as high capital costs compared to the internal combustion engine (ICE) cars [6] and longer refueling times. There is also the potential for negative impacts on the electrical grid if the EV charging is unregulated [7].

One way proposed to mitigate negative charging impacts of EVs and to lower their total lifetime cost is Vehicle-to-Grid (V2G) [8]. V2G is defined as the provision of energy and ancillary services from an EV to the grid [9]. There are two types of proposed V2G operations [10]. The first method is unidirectional V2G [11], in which EVs are treated as controllable loads for providing grid operators with ancillary services and charging at off-peak periods. The second is bidirectional V2G, which allows the EVs to charge and discharge their batteries to provide grid support.

A single EV does not have enough capacity to participate in most electricity markets [12]. Therefore, EV owner participation in electricity markets needs to be facilitated through aggregators [13], [14]. Aggregation also decreases the forecasting uncertainty of the hourly EV availability for delivering electric power to the market [15]. It provides the additional flexibility for market participants to potentially opt out during unforeseen conditions. The EV Aggregato's (EVA) main function is to act as an intermediary between the market operator and EV owners. The EVA sends energy bids to the futures energy market, purchases energy from the energy market at market price and sells this energy to the EV owners. The EVA can also use EV charging to participate in ancillary services (AS) markets by offering regulation up/down and responsive reserves. If the bids are accepted by the AS markets, the EVAs respond in real-time to market signals provided by system operators. In such cases, the EVAs respond by adjusting EV charging.

The EVA's objective is to maximize its payoffs while satisfying operational and contractual constraints. Hence, it is important to develop optimization models for the planning and operations of EV aggregation in electricity markets. The optimization of the operation process determines the optimal hourly charging and discharging strategies by an EVA that maximize the EVA's payoffs. Several studies have attempted to determine most suitable operational bidding strategies for an EVA in electricity markets. In [16] and [17], unidirectional V2G bidding regulation and responsive reserves were investigated. The work was extended in [18] to consider bidirectional V2G, in which the depreciation cost of batteries was taken into account. More recent works on operational bidding strategies include [19]–[22]. These works demonstrated the operational feasibility of an existing EVA. However, they did not study the feasibility of investment in establishing EVAs.

Few researches have recently targeted EV planning. Their focus has been mainly on optimally locating EV charging stations [23–[25]. In [23], a multi-objective evolutionary algorithm was used to locate the charging stations in a radial distribution system for a known number of EVs. In [24], renewable resources (wind and solar), ESS, and EV charging stations were integrated into a second-order conic model where the objective was to minimize the system's power losses. Reference [25] integrated ESS in the charging stations to facilitate EV charging and considered the life cycle of the ESS. Note that [23–[25] used non-linear models and assumed the number of EVs to be pre-determined. Moreover, they did not consider identifying the best incentives for EV owners from the EVA's perspective. Another option to provide AS to the electricity markets is by using a dedicated energy storage system (ESS) with sufficient energy and power capabilities [26]. Few works have tackled the planning aspects of ESS. In [27], ESS planning was approached from a centralized system operator's standpoint. The intent was to find the optimal ESS energy and power capacities that minimize the system operator's investment and operational costs. However, the market-based environment was not considered and the ESS was not meant to provide AS. A control strategy for using ESS to support wind power plants in providing frequency regulation service was proposed in [28] while reducing the sizing and increasing the lifetime of the storage system. In [29], the sizing of operation of an ESS that was used for providing spinning reserve and thus regulating the frequency in an isolated system with low inertia was optimized. However, the focus in [28] and [29] was in establishing the control strategy that resulted in a reduced ESS size rather than proposing a comprehensive ESS planning model. In [30], ESS was also considered for participating in a primary frequency control market with the aim of maximizing the payoffs by optimally sizing and controlling ESS energy. However, ESS power capacity sizing was neglected.

ESS can also contribute to dynamic support services, such as flexible ramping product (FRP), due to its fast-responsive characteristics. Reference [31] proposed a model for ESS aggregators to maximize their profits by bidding ramping up/down capacities in the day-ahead market. FRP services are initially considered as a marketable product in the US by some independent system operators (ISO), such as California ISO (CAISO) and Midcontinent ISO (MISO) [32], [33]. FRP aggregators submit either up or down capacities to the system operator on a day-ahead basis. Those capacities are called upon in real time by receiving a signal once each several minutes, e.g. every five minutes in CAISO [31]

To the best of the authors' knowledge, EVA and ESS planning for AS provision in a market environment have not yet been comprehensively studied. Therefore, the main contributions of this paper are

1. A linear planning model that assists investors who consider investing in EV aggregation for the purpose of AS provision to electricity markets is proposed. This model aims to assess the investment feasibility in establishing an EV aggregator. The planning model identifies as decision variables the best incentives to be offered by the EVA to EV owners and the number of targeted EVs. It should be noted that none of the existing EV planning models reported in the literature, e.g. [23]–[25], have identified these two important planning decisions as decision variables
2. The proposed EVA planning model considers various factors, including communication infrastructure costs, battery depreciation costs (which includes the cost of battery degradation due to cycling), and the cost of required additional hardware that enables bidirectional V2G. It also takes technical and market constraints into consideration.
3. A linear planning model for investing in a dedicated ESS to participate in AS markets is proposed. The aim is to decide on the best ESS power and energy capacities, considering the investo's budget constraints. To ensure fair comparisons, both options (EVA and ESS) are assumed to have the same investment costs
4. This is the first study that compares the two options (EVs and ESS) from an investor's standpoint and helps decide which one is the most profitable. Sensitivity analyses are also carried out in each case to study the impact of key parameters on the investments.
5. In addition, the optimal operational decisions for the EVs and ESS, including the optimal bidding capacities and operating points, are also determined using the proposed model.
6. This paper includes the modeling of dynamic support services (DSS) bidding, namely flexible ramping product (FRP), in the day-ahead market (DA). The effects of including these services on the optimal profits are also studied

The rest of the paper is organized as follows: The details of the proposed planning model for EV aggregation are provided in section III. The optimization model for ESS planning is detailed in section IV. A case study that assesses the two investment options in the electricity market in addition to the proposed results are given in sections V and VI, respectively. Finally, a few concluding remarks are given in Section VII.

II. PROPOSED PLANNING MODEL FOR EV AGGREGATION

In this section, the EV aggregation planning model is presented. The EVA planning optimization problem is presented in Sections III.A and III.B. Since the optimization function is non-convex, we develop a methodology to deal with this non-convexity, as presented in Section III.C.

A. EV AGGREGATOR'S OBJECTIVE FUNCTION

It is assumed that the EVA intends to participate in a pool-based market. It is expected to submit energy bids to the day-ahead energy market, AS capacity, and dynamic support services; namely FRP. Each bid is to be cleared in its concerned pool-based market mechanism. The EVA's expected daily income and cost are given in (1) and (2). The first term in (1) represents the revenue from participating in AS markets to provide regulation down, up, and reserve capacities, in addition, to participate in DSS market by providing ramping up/down. The second term represents the revenue from selling energy to EV owners in order to charge their EVs. This term turns negative when the EV is being discharged. The first term in (2) represents the cost of buying energy from the grid for EV charging (negative when EV is being discharged). The second term is the cost paid to EV owners to compensate them for EV battery depreciation during discharging.

Each participating EV has a modeled weekday commute profile that consists of a morning trip and an evening trip for weekdays, and two random trip times on the weekend. Each weekday trip is assumed to take place at approximately the same time each day. Due to uncertainty in trip time, the EV is unavailable during that whole scheduling hour. Additionally, each EV has a chance of an unexpected departure which makes them unavailable during a random number of future hours. At 2 AM, all EVs are assumed to be plugged in and charging until 6 AM. Note that v is defined for each EV at each hour in order to restrict V2G services to whenever the EV is available. The possibility of random hourly EV departure is taken into account by calculating the percentage of remaining EVs to perform V2G at each hour (ω_t). Note that ω_t is a function of the accumulated probability of random departure of all EVs at hour t, π_{it}^A, which, in turn, is a function of the time of scheduled trips for each EV during the day (3), (4). In (4), π_{it}^A is reset at each scheduled trip time τ_i^p because it is assumed that the availability of an EV at these time slots is known with certainty. The EVA's capacity of providing regulation down, up, reserve, and ramping up/down are given by (5),(6),(7),and (6). Similarly, R^R is defined as functions of AP^R in (9). The expected power draw is defined in (10).

The constraint (11) implies that the EV battery depreciation cost g (afforded to EV owners for performing V2G services) is positive only when the EV is discharging. Otherwise, it is zero. Note that a more conservative estimate for the expected power draw, $E\left[FP_{itdw}^{-}\right]$ defined in (12), is used to obtain g, where the power draw is only affected by the regulation up and responsive reserve services [18].

Using batteries to perform ancillary services reduces the battery life due to the increased cycling. Additionally, the discharge current rate and the current SOC at the time of discharge also affect this degradation. As the ancillary services dispatch cannot be known a priori, the costs associated with ancillary service degradation are modeled as an average cost per kW of energy discharged while performing ancillary services (13). Equation (13) uses the average degradation cost developed in [34] as its first term. This is a linear cost, but it can be piecewise linear if more detailed, charge rate dependent costs are available. The second term of (13) is the cost of the lost energy due to cycling, developed in [18], which must be paid by the aggregator.

$$\begin{aligned} OpI_{dw} &= \sum\nolimits_{t=1}^{T} \omega_t \left(\sigma_{tdw}^{D} R_{tdw}^{D} + \sigma_{tdw}^{U} R_{tdw}^{U} \right. \\ &\quad \left. + \sigma_{tdw}^{R} R_{tdw}^{R} + \sigma_{tdw}^{RAU} R_{tdw}^{RAU} + \sigma_{tdw}^{RAD} R_{tdw}^{RAD}\right) \\ &\quad + \beta \sum\nolimits_{t=1}^{T} \omega_t \sum\nolimits_{i=1}^{NA} E\left[FP_{itdw}\right] \qquad (1) \end{aligned}$$

$$\begin{aligned} OpC_{dw} &= \sum\nolimits_{t=1}^{T} \omega_t \sum\nolimits_{i=1}^{NA} \sigma_{tdw}^{E} E\left[FP_{itdw}\right] \\ &\quad + \sum\nolimits_{t=1}^{T} \sum\nolimits_{i=1}^{NA} g_{itdw} \qquad (2) \end{aligned}$$

$$\omega_t = 1 - \frac{1}{NA} \sum\nolimits_{i=1}^{NA} \pi_{it}^{A} \qquad (3)$$

$$\begin{aligned} \pi_{it}^{A} &= \sum\nolimits_{h=\tau_i^{p-1}}^{t} \pi_{ih},\ \tau_i^{p-1} \le t < \tau_i^{p} \quad \text{where} \\ &\quad \tau_i^0 = 1, \quad p = 1, 2, \ldots, NP \qquad (4) \end{aligned}$$

$$R_{tdw}^{D} = \sum\nolimits_{i=1}^{NA} AP_{itdw}^{D} \qquad (5)$$

$$R_{tdw}^{U} = \sum\nolimits_{i=1}^{NA} AP_{itdw}^{U} \qquad (6)$$

$$R_{tdw}^{RAU} = \sum\nolimits_{i=1}^{NA} AP_{itdw}^{RAU} \qquad (7)$$

$$R_{tdw}^{RAD} = \sum\nolimits_{i=1}^{NA} AP_{itdw}^{RAD} \qquad (8)$$

$$R_{tdw}^{R} = \sum\nolimits_{i=1}^{NA} AP_{itdw}^{R} \qquad (9)$$

$$\begin{aligned} E\left[FP_{itdw}\right] &= (POP_{itdw} + \alpha_{itdw}^{D} AP_{itdw}^{D} \\ &\quad + \alpha_{itdw}^{RAD} AP_{itdw}^{RAD} - \alpha_{itdw}^{U} AP_{itdw}^{U} \\ &\quad - \alpha_{itdw}^{RAU} AP_{itdw}^{RAU} - \alpha_{itdw}^{R} AP_{itdw}^{R}) v_{it} \qquad (10) \end{aligned}$$

$$g_{itdw} = \max(-DC_i E\left[FP_{itdw}^{-}\right] \delta_{it}/\eta_i, 0) \qquad (11)$$

$$\begin{aligned} E\left[FP_{itdw}^{-}\right] &= (POP_{itdw} - \alpha_{itdw}^{U} AP_{itdw}^{U} \\ &\quad - \alpha_{itdw}^{RAU} AP_{itdw}^{RAU} - \alpha_{itdw}^{R} AP_{itdw}^{R}) v_{it} \qquad (12) \end{aligned}$$

$$DC_i = 0.042\,(BatC/312) + \beta\left(1 - \eta_i^2\right)/\eta_i \qquad (13)$$

$$\delta_{it} = (1 - \pi_{it})^{-1} \qquad (14)$$

In order to estimate annual payoffs, weighted representative weeks are used [35]. Each representative week is weighted by a factor K_w and the sum of all factors is equal to the total number of weeks in a year. The annual payoff for a number of representative weeks, NW, is given in (15). The EVA's investment includes the costs of communication infrastructure, smart meter, and retrofitting the EV charger to a new one that is capable of bi-directional power flow as given in (16) [36]. Hence, the present worth of the total payoff from investing in EV aggregation for the project time span is given by (17), where r is the discount rate and NY is the project's time horizon. It is assumed that the investment cost is paid at the start of the project.

$$OpP_y = \sum\nolimits_{w=1}^{NW} K_w \sum\nolimits_{d=1}^{7} (OpI_{dw} - OpC_{dw}) \qquad (15)$$

$$InvC = \sum\nolimits_{i=1}^{NEV} (SC + ComC + BiC \cdot MP_i) \qquad (16)$$

$$TP = \sum\nolimits_{y=1}^{NY} (1+r)^{-y} \cdot OpP_y - InvC \qquad (17)$$

B. OPTIMIZATION MODEL FOR EVA PLANNING

The complete formulation of payoff maximization for the EVA planning case is

$$\text{Maximize } TP \tag{18}$$

$$\text{Subject to } SOC_{it} = SOC_{i,t-1} + E\left[FP_{itdw}\right]\delta_{it}\eta_i - E_{it} \tag{19}$$

$$\varphi_i MC_i \le SOC_{it} \le MC_i, \quad \forall t \le T-1 \tag{20}$$

$$\Phi_i MC_i \le SOC_{iT} \le MC_i \tag{21}$$

$$\left(POP_{itdw} + AP^{D}_{itdw} + AP^{RAD}_{itdw}\right)\delta_{it}\eta_i \le MC_i - SOC_{it} \tag{22}$$

$$\left(POP_{itdw} - AP^{U}_{itdw} - AP^{RAU}_{itdw} - AP^{R}_{itdw}\right)\delta_{it}\eta_i + SOC_{it} \ge E_{it} \tag{23}$$

$$\left(POP_{itdw} + AP^{D}_{itdw} + AP^{RAD}_{itdw}\right)\delta_{it} \le MP_i v_{it} \tag{24}$$

$$POP_{itdw} - AP^{R}_{itdw} - AP^{U}_{itdw} - AP^{RAU}_{itdw} \ge -v_{it}\max(MP_i SOC_{it}) \tag{25}$$

$$AP^{D}_{itdw}, AP^{U}_{itdw}, AP^{R}_{itdw} AP^{RAD}_{itdw} AP^{RAU}_{itdw} \ge 0 \tag{26}$$

$$POP_{itdw} \ge -v_{it}\max(MP_i SOC_{it}) \tag{27}$$

$$\left|SOC_{itdw} - SOC_{i,t-1,d,w}\right| \le v_{it} MP_i/\eta_i \tag{28}$$

In (19), the energy stored in the EV battery at hour t is a function of the energy available in the battery from the previous hour, the expected power draw to charge/discharge the battery at t, and the energy used during a scheduled trip at t (if any). It is assumed that when an EV undergoes a trip at hour t, it won't be available for charging/discharging at that hour (i.e. if $E_{it} > 0$, $v_{it} = 0$, and $E\left[FP_{itdw}\right] = 0$). Relation (20) states that the SOC of an EV battery will be, at all time, within acceptable limits based on the battery energy capacity, MC_i, and customer-defined minimum SOC, φMC_i, set for driving purposes. Constraint (21) states that the final SOC must be at least ΦMC_i, where Φ is also customer-defined; $0 \le \varphi \le \Phi \le 1$.

Constraint (22) represents the relation between EV energy limits and battery decision variables. The relation limits the EVA's ability to bid regulation down capacity to within energy remaining in the battery. Relation (23) ensures that sufficient charges are available for EVs' scheduled trips. Constraints (24)-(28) represent relations among battery power limit, MP, and decision variables POP, AP^D, AP^U, AP^R, AP^{RAD} and AP^{RAU}. Constraint (28) states that the EVs cannot violate the charged power limit when performing V2G services.

The optimization problem stated in (1)-(28) includes two sets of decision variables. The operation decision variables, POP, AP^D, AP^U, AP^R, AP^{RAD} and AP^{RAU} are associated with each hour in the planning horizon. The Long-term planning decision variables are β and NA only.

Note that (1)-(28) represents a non-convex optimization problem. In (1), the tariff β, a decision variable, is multiplied by $E\left[FP_{itdw}\right]$, which is a function of the decision variables POP, AP^D, AP^U, AP^R, AP^{RAD} and AP^{RAU}. A similar issue appears in (11). In the next section, a methodology for addressing this non-convex optimization issue is presented.

C. EVA'S SELECTION OF ENERGY TARIFF FOR ENERGY PURCHASE (β)

The EVA decides on an energy tariff, β, to be collected from the EV owners for their energy purchases. A higher tariff results in a higher income from charging an EV. However, higher tariffs reduce the percentage of EV owners who will be willing to participate in the EV aggregation program, γ. This affects the EVA's profitability in AS markets, which is a function of the total number of participating EVs.

The models that relate charging tariffs to EV owners' willingness to participate in EV aggregation are often a function of the prevailing circumstances in specific markets and mostly determined by societal and economic issues pertaining to a region. In this work, it is assumed that there is a linear relation between β and γ. It is assumed that the fixed charging tariff ranges between $\beta_{min} = 0$ and $\beta_{max} = 0.12$ \$/kWh [22]. It is also assumed that γ is zero at $\beta = \beta_{max}$, since there is no incentive for the EV owners to participate. γ is assumed to peak at $\beta = \beta_{min}$, which means that the EVA charges EVs at no cost and depends solely on market revenues for its payoffs.

The proposed γ vs. β relation is given in (29), where m is a negative slope, given in (30), and γ_o is the percentage of EVs that would participate in aggregation if the EVA offered to charge their vehicles for free. Figure 1 shows five possible realizations of the proposed γ–β relation. For example, for Line 1, $\gamma_o = 0.2$.

$$\gamma = \gamma_o + m\beta \tag{29}$$

$$m = \left(\frac{-\gamma_o}{\beta_{max} - \beta_{min}}\right) \tag{30}$$

Assuming that the EVA's region contains NT number of EVs, the number of participating EVs in aggregation, NA, is

$$NA = \gamma NT \tag{31}$$

In order to obtain the optimal β and NA, sequential linearization is sought. The following procedure is performed:

1- Assume γ_o. Calculate m using (30)
2- Set $\beta = 0$.
3- Obtain γ using (29), then obtain NA using (31).
4- Solve (1)–(28) to obtain $InvC(\beta NA)$ and $TP(\beta NA)$
5- Increase β by an increment of $\Delta\beta$
6- Repeat Steps 3–5. If $\gamma = 0$ is reached, go to step 7.
7- Compare TP obtained in Steps 1–6 and identify the optimal β and NA corresponding to the assumed γ_o
8- Assume a new value for γ_o and calculate m. Repeat Steps 2–7.

Note that this procedure turns the non-convex optimization model presented in Section III.B into a sequence of linear programs. Specifically, by setting the value of β according to the procedure described above prior to running the optimization, the model (1)-(28) becomes linear. Thus, it can be efficiently solved using any of the available commercial optimization packages.

To reduce the computational burden, an EV fleet that consists of a reduced number of EVs, NEV, is used. The reduced EV set is obtained by grouping EVs that behave similarly. For scaling, the optimization problem (1)–(28) needs to be modified. The fleet parameters (total energy and power capacities) and the parameters of each EV (π, δ_{it}, ω) are scaled to represent a larger fleet. The scaling factor, SF, for scaling the EV fleet's parameters is given as

$$SF = \frac{NA}{NEV} \tag{32}$$

This scaling factor scales the probability of a random EV departure at hour t stated as

$$S\pi_i = \frac{\pi_i}{SF} \tag{33}$$

Therefore, in the down-scaled version of (1)–(28), π_i is replaced by $S\pi_i$ in (4) and (14), and NA is replaced by NEV in (1)–(5). After the down-scaled version of (1)–(28) is solved, the resulting total payoffs is scaled up by multiplying it by SF.

III. OPTIMIZATION MODEL FOR ESS PLANNIN

For an investor choosing to use a dedicated ESS for provision of AS in electricity markets, the planning optimization model is presented in (34)-(54). This model is derived from the EVA model presented in (1)-(28) after considering a number of observations. First, this model assumes that a single ESS is used i.e. $i = 1$. Since the ESS is stationary, it is available all the time, or $v_{it} = 1\ \forall t$. In addition, the dedicated ESS makes revenues only by participating in markets. Hence, the last term in (1) is dropped. Moreover, since the ESS is stationary and is always available for participation, there is no need to consider random availability (that is, $\delta_t = 1$ and $\omega_t = 1 \forall t$). Therefore, the ESS daily expected income and cost are given by (35) and (36), respectively.

The differences in energy storage constraints compared to that of EVAs are rather minor. One difference is that there is no need to include the energy for planned trips in the SOC relation (compare (43) to (19)). The SOC of ESS does not have to be almost fully charged at the end of the operation day, as (21) and (45) imply. In this work, the ESS is at least half-charged at the end of the operation day. Inequalities (53) and (54) are to define the maximum energy and power capacity limits

Note that the ESS investment cost represents the cost of procuring ESS energy (MC) and power capacities (MP). The ESS investment cost is, therefore, given by (42). As such, for a fixed, pre-determined investment cost ($InvC$), an investment in one capacity will limit the investment in the other. In this work, the comparison of investment on ESS and EVA is based on using the same fixed investment cost for both options. To perform this comparison, the following procedure is followed:

1- Obtain the ESS investment cost based on the EVA's planning optimization and use it as an input for the ESS planning optimization. That is, equate $InvC$ in (42) to $InvC(\beta NA)$ obtained from Step 4 of the EVA planning procedure described in Section III-C.
2- Assume a small ESS energy capacity, MC.
3- Use (42) to obtain the related power capacity, MP.
4- Solve (34)–(54) to obtain $TP(MCMP)$
5- Increase MC
6- Repeat Steps 3–5. If $MP = 0$ is reached, go to step 7.
7- Compare TP obtained in Steps 1–6 and identify the optimal MP and MC corresponding to this pre-set $InvC$

$$\text{Maximize } TP = \sum\nolimits_{y=1}^{NY} (1+r)^{-y} \cdot OpP_y - InvC \tag{34}$$

where

$$\begin{aligned} OpI_{dw} &= \sum\nolimits_t \Big(\sigma^D_{tdw} AP^D_{tdw} + \sigma^U_{tdw} AP^U_{tdw} + \sigma^{RAU}_{tdw} AP^{RAU}_{tdw} \\ &\quad + \sigma^{RAD}_{tdw} AP^{RAD}_{tdw} + \sigma^R_{tdw} AP^R_{tdw}\Big) \end{aligned} \tag{35}$$

$$OpC_{dw} = \sum\nolimits_t \sigma^E_{tdw} E\left[FP_{tdw}\right] + \sum\nolimits_t g_{tdw} \tag{36}$$

$$\begin{aligned} E\left[FP_{tdw}\right] &= (POP_{tdw} + \alpha^D_{tdw} AP^D_{tdw} + \alpha^{RAD}_{tdw} AP^{RAD}_{tdw} \\ &\quad - \alpha^U_{tdw} AP^U_{tdw} - \alpha^{RAU}_{tdw} AP^{RAU}_{tdw} - \alpha^R_{tdw} AP^R_{tdw}) \end{aligned} \tag{37}$$

$$g_{tdw} = \max(-DC \cdot E\left[FP^-_{tdw}\right]/\eta, 0) \tag{38}$$

$$\begin{aligned} E\left[FP^-_{tdw}\right] &= (POP_{tdw} - \alpha^U_{tdw} AP^U_{tdw} - \alpha^{RAU}_{tdw} AP^{RAU}_{tdw} \\ &\quad - \alpha^R_{tdw} AP^R_{tdw}) \end{aligned} \tag{39}$$

$$DC = 0.042\,(BatC/312) \tag{40}$$

$$OpP_y = \sum\nolimits_{w=1}^{NW} K_w \sum\nolimits_{d=1}^{7} (OpI_{dw} - OpC_{dw}) \tag{41}$$

$$InvC = ChC \cdot MP + EnC \cdot MC \tag{42}$$

Subject to

$$SOC_t = SOC_{t-1} + E\left[FP_{tdw}\right]\eta \tag{43}$$

$$\varphi MC \le SOC_t \le MC, \quad \forall t \le T-1 \tag{44}$$

$$\Phi MC \le SOC_T \le MC \tag{45}$$

$$\left(POP_{tdw} + AP^D_{tdw} + AP^{RAD}_{tdw}\right)\eta \le MC - SOC_t \tag{46}$$

$$\left(POP_{tdw} - AP^U_{tdw} - AP^{RAU}_{tdw} - AP^R_{tdw}\right)\eta + SOC_t \ge 0 \tag{47}$$

$$\left(POP_{tdw} + AP^D_{tdw} + AP^{RAD}_{tdw}\right) \le MP \tag{48}$$

$$POP_{itdw} - AP^R_{tdw} - AP^U_{tdw} - AP^{RAU}_{tdw} \ge -MP \tag{49}$$

$$AP^D_{tdw}, AP^U_{tdw}, AP^R_{tdw} AP^{RAD}_{tdw} AP^{RAU}_{tdw} \ge 0 \tag{50}$$

$$POP_{tdw} \ge -MP \tag{51}$$

$$\left|SOC_{tdw} - SOC_{t-1,d,w}\right| \le MP/\eta \tag{52}$$

$$MP \le MP_{Max} \tag{53}$$

$$MC \le MC_{Max} \tag{54}$$

IV. CASE STUDY

The case study examines the two investment options in the electricity market. Planning aspects, such as the investment cost, discount rate and the project lifetime are also considered. A year is represented by representative weeks which are weighed by scaling factors and the sum of these factors must equal 52. For this study, three representative weeks are selected, and the three selected weeks are scaled by the same factor ($K_w = 17, \forall w$). The selection of representative weeks is based on the minimum Euclidean distance between weekly energy prices and energy prices for the remaining weeks. We choose the energy price as a criterion because of its significant effect on bidding strategies and payoffs of EVA/ESS. This market-based evaluation is assumed to be for an investor who is based in Houston, Texas, with more than 70,000 EVs by the year 2020 [37]. The EV fleet is comprised of 50% Nissan Leaf, 20% Mitsubishi i-MiEVs and 30% Tesla Model S, all with $\eta = 90\%$. Each EV is assigned one of 50 different energy usage profiles based on statistical driving behaviors in urban Texas [38]. The investment costs are taken from [36] considering the costs of communication infrastructure, smart meters, and retrofitting EV chargers to handle bi-directional power flow for EVAs (assuming 1 euro = \$1.245). It is assumed that all EV owners are to set φ and Φ at 0.1, and 0.99, respectively.

All forecasted data is taken from the Electric Reliability Council of Texas (ERCOT). Because the dynamic support services, such as FRP, are still not supported in the studied market, they are ignored in sections VI.A, B, and C. A case study is included in section VI.D to show the result of the optimization model if those services are introduced in ERCOT. The ramping up/down prices are assumed to be 5 \$/MWh and the deployment signal to be 0.5.

The investment cost for the ESS is considered to be the same as the bidirectional cost of EVAs. This is based on the assumption that the cost of retrofitting the EV charger from the unidirectional charging to bidirectional charging is equal to the bidirectional inverter cost in the year 2020. The other investment cost for ESS is the energy capacity cost at the year 2020. Because all EVs use Lithium-ion batteries, it is assumed that Lithium-ion batteries are also used for energy storage. According to [39], the price range for Lithium-ion batteries is expected to be between 200 and 400 \$/kWh by the year 2020. In the base case, the energy capacity price of 200 \$/kWh is used. A lifetime of 12 years and a discount rate of 5% are used for both cases. This lifetime corresponds to the approximate average age of the light duty vehicle fleet in the USA [40]. While this number is slightly higher than the current expected lifespan of Li-ion batteries, it is expected to be attainable in the future with proper battery management [41]. Table 1 summarizes the parameters used in this study for the base case. The optimization problems were solved using CVX, which is a MATLAB-based convex optimization toolbox [42]. The simulations were carried out on an intel core i7 2.9-GHz, 8-GB RAM PC.

TABLE 1. Parameters and constants.

Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
K_w	17	NT	70k	$BatC$	200	r	5%
NEV	50	T	24	$ComC$	88.4	η	0.9
NY	12	BiC	186.7	ChC	186.7	φ	0.1
NW	3	EnC	200	SC	36.1	Φ	0.99
MC_{Max}	190k	MP_{Max}	190k				

V. RESULT

The comparison of the two investment options from planning aspects is performed by finding the optimal fixed charging tariff, β, that makes the highest payoffs, TP, for the EVA case. This is done for five values of γ_o (0.2, 0.4, 0.6, 0.8, and 1.0), as shown in figure 1. For each assumed value of γ_o, the sequential optimization outlined in Section III-C is performed to obtain the optimal payoffs, TP, and the corresponding investment costs, $InvC$, corresponding to that γ_o. This EVA's investment cost is used as an investment cost limit for the ESS case. Then, the procedure outlined in Section IV is followed to determine the optimal ESS payoffs and corresponding power and energy capacities. The maximum payoffs of the EVA and ESS for all cases are compared to decide on the most profitable investment. Then, sensitivity analyses are carried out to study the impact of key parameters on optimal solutions.

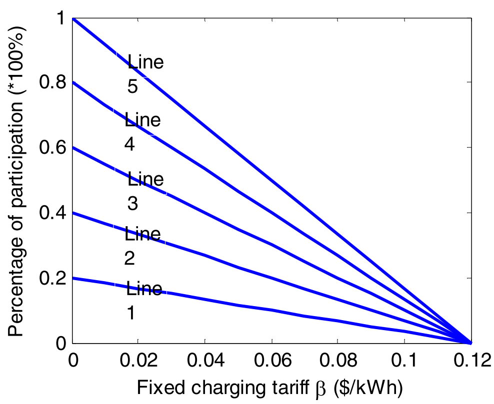

FIGURE 1. Relation between the charging tariff and participation level for $\gamma_o = 0.2, 0.4, 0.6, 0.8$, and 1.0.

A. EV AGGREGATOR CASE

In this sub-section, sample results obtained for the EVA case are presented. These results are obtained from setting $\gamma_o = 0.6$, then sequentially solving (1)-(28) following the procedure presented in Section III-C, where the increment $\Delta\beta$ is chosen to be 0.01. The simulation time needed to carry out the sequential optimization procedure is about 36 hours. Note that a smaller increment would give rise to more refined results. However, that would increase the required computational time. The EVA's payoffs vs. fixed charging tariffs (TP vs. β) are shown in figure 2. It is clear that an EVA obtains the highest payoffs when it charges EV owners at a moderate fixed charging tariff. Low payoffs arise at very low or very high charging tariffs. Figure 2 shows that the highest payoffs occurs at $\beta = 0.05$ \$/kWh and EV participation of $\gamma = 35\%$. The investment cost for this case is \$41.06 million. This is

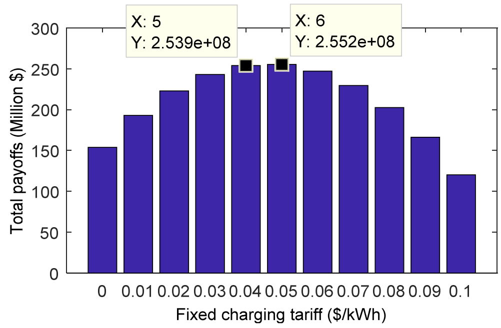

FIGURE 2. EV's payoffs vs. β for a max. participation of 60% ($\gamma_o = 06$).

the cost of communication infrastructure, smart meter, and retrofitting the EV charger to handle bi-directional power flow, as stated in (16), for 24500 EVs (35% of the total considered of 70000 EVs). Figure 3 and figure 4 show the operational decision variables (AP^D, AP^U, AP^R, SOC, POP) in a typical day for one of the studied EV (Tesla Model S) with an 85-kWh battery capacity and 20-kW bi-directional charger.

B. ENERGY STORAGE SYSTEM CASE

The procedure outlined in Section IV is used next. The investment cost obtained from the EVA case ($41.06 million) is used as an investment cost limit for the ESS case such that (42) is met. If the investment cost is used for acquiring power capacity only (with zero energy capacity), the resulting MP is 219.9 MW. Therefore, the range of MP examined is 0.1 to 219.9 MW, with 0.1 MW increments. The maximum payoff is obtained for each case and the corresponding MP and MC for the case with the highest payoff is identified. The range of energy and corresponding power capacities for all optimization cases are shown in figure 5. The ESS optimization results are shown in figure 6.

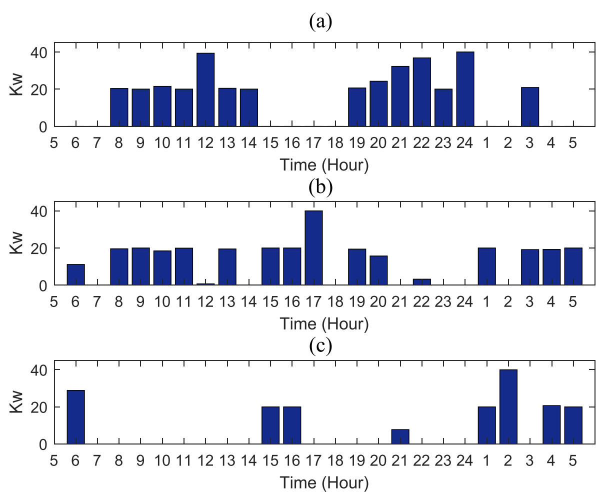

FIGURE 3. EV bidding capacity for (a) regulation up, (b) down, and (c) reserve in a typical day for $\beta = 0.05$.

Figure 6 indicates that the payoffs are negative for low power capacities. This is because a very low power capacity leads to low market bids, see (48) and (49). On the other hand, extremely low energy capacities also result in negative or low payoffs since AS bids will be constrained by the available energy capacity, see (44)-(46). The optimal point is where the energy and power capacities are 111 MWh and 101 MW, with a payoff of $39.78 million.

Note that the payoff of the ESS ($39.78 million) is 84.4% lower than that of EVA ($255 million) for the same investment cost. This result indicates that investing in EV aggregation is, in this case, more profitable than investing in ESS for the participation in AS markets. The reason for the low ESS payoffs are the limited power and energy capacities that can be purchased by the investor.

The same procedures for the EVA and ESS cases are repeated for $\gamma_o = 0.2, 0.4, 0.8$, and 1.0, and the corresponding results are summarized in Table 2. These results indicate that Investing in EVAs to provide ancillary services is consistently more profitable than investing in ESS.

TABLE 2. Comparison of investing in EV aggregators and ESS.

Line	Investment cost (Millions$)	Optimal Power Capacity (MW)	Optimal Energy Capacity (MWh)	Energy Storage Payoff (Millions$)	EV Aggregator Payoff (Millions$)
1	13.68	33.6	37	13.26	85
2	27.37	67.3	74	26.51	170
3	41.06	101.0	111	39.77	255
4	54.74	134.7	148	53.04	340
5	68.43	168.3	185	66.30	425

C. SENSITIVITY ANALYSES

This section studies the effect of varying the assumed values of key parameters on the results presented in the previous two sub-sections. All comparisons are based on $\gamma_o = 0.6$. Similar trends are observed when these analyses are done for other values of γ_o, whose results are not reported due to space limitations.

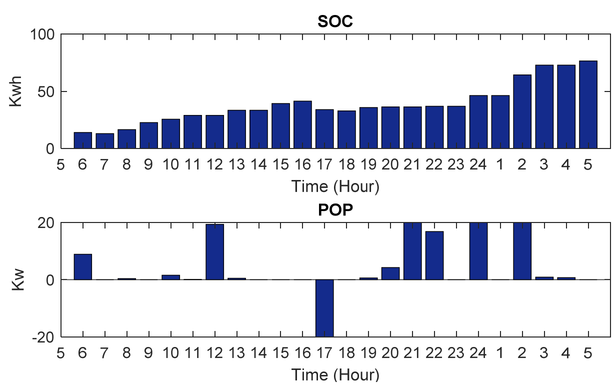

FIGURE 4. EV SOC and POP in a typical day for β =0.05.

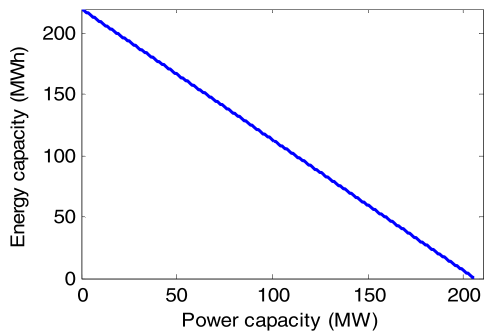

FIGURE 5. Energy vs. power capacities for an ESS, using a fixed investment cost obtained from the EVA planning optimization with $\gamma_o = 06$.

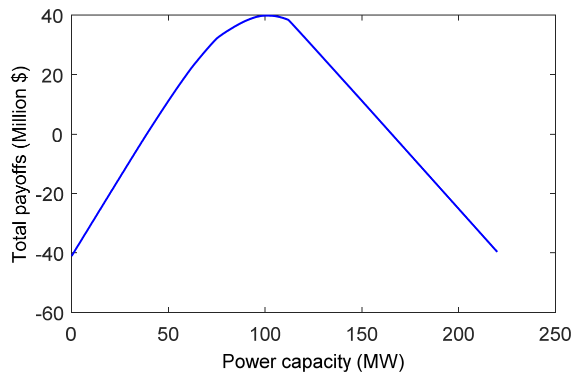

FIGURE 6. ESS payoffs for different combinations of power and energy capacities, using a fixed investment cost obtained from the EVA planning case, $\gamma_o = 06$.

1) EFFECT OF CHANGING THE POWER CAPACITY COST

In the base case, the power capacity cost used is 186.7 \$/kW. If the power capacity cost is doubled, the corresponding TP vs. β is shown in figure 7. The results show that the optimal payoffs drop by 14.9% from \$255 million to \$217 million. It is interesting to note that the optimal β does not change. The lower payoff can be explained by the increase in the investment cost to \$79 million, a 48.1% increase.

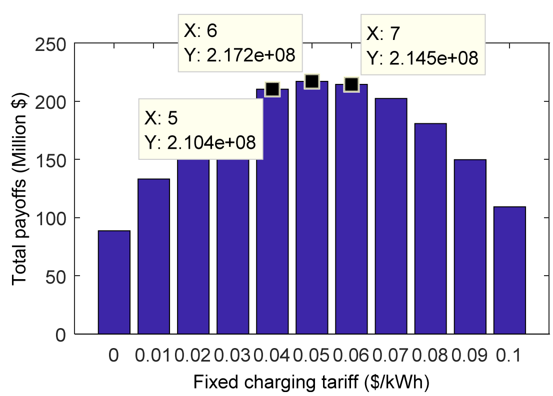

FIGURE 7. Aggregator's payoffs vs. β after the power cost is doubled.

For the ESS case, the payoff curve is very similar in shape to that of figure 6. However, the optimal ESS payoff drops by 26.9% from \$39.78 million to \$29.07 million. The optimal energy and power capacities for the new case are 162.3 MWh and 124.8 MW, which are larger than the original optimal capacities because of the higher investment cost. These results indicate that the investment on ESS is more sensitive to changes in power capacity cost.

2) EFFECT OF CHANGING THE ENERGY CAPACITY COS

The energy capacity cost is also used in both cases. It represents the battery replacement cost for EVAs and the energy capacity cost for ESS. The energy capacity cost is doubled from that used in the base case. The results are shown in figure 8. The EVA payoffs drop by only 0.78% from \$255 million to \$253 million, indicating that changing the battery replacement cost for EVAs does not affect the payoffs significantly. This is because the battery replacement costs are not included in the investment cost. Rather, it is included in battery depreciation cost, g, and discharging is done only occasionally in real-time, as shown in figure 9 (the hourly expected power draw for all EVs on average).

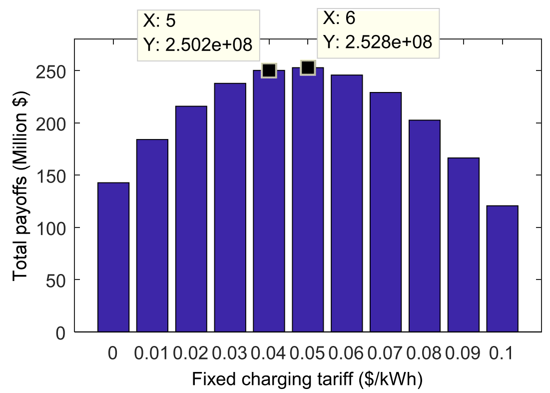

FIGURE 8. Aggregator's payoffs vs. β after the energy cost is doubled.

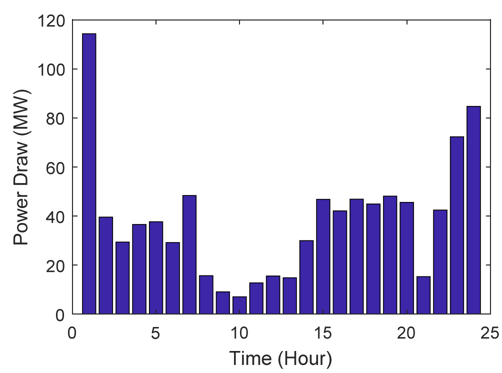

FIGURE 9. The average expected power draw by EVs for an average day $\gamma_o = 06$.

For the ESS case, doubling the energy cost has a significant effect on payoffs, which drop by 75.3% from \$39.78 million to only \$9.82 million. The optimal energy and power capacities are 69.3 MWh and 71.4 MW, respectively. This significant drop in ESS payoffs is because energy cost directly affects the investment cost of ESS.

3) EFFECT OF CHANGING THE MINIMUM ACCEPTABLE SOC LEVE

This section studies the effect of assuming a higher minimum acceptable SOC level, φ, on payoffs. The value of φ is increased from 0.1 to 0.5. The results of this case for the EVA are shown in figure 10, which demonstrates that the value of φ has a major effect on the optimal EV charging tariff by EVAs. β is reduced from 0.05 \$/kWh in the original case to 0.03 \$/kWh. This reduction reflects the fact that EVAs would need to attract more EV owners (7000 EVs more than the base case of 24500 EVs) to participate in aggregation because the higher φ reduces the EVAs' available AS capacities. This forces the EVA to recruit a larger portion of available EV owners to mitigate the effect of the higher φ. The payoffs in this case drop by 12% from \$255 million in the base case to \$224 million. For the ESS case, the payoffs are increased by 19% to \$49.19 million. This increment is explained by the fact that the investment cost for EVAs has increased as a result of reducing the EV charging cost, which increased the number of participating EVs into the aggregation program. Since the investment cost is fixed for the two case studies, the ESS payoffs have increased. The optimal energy and power capacities are 144.6 MWh and 127.8 MW, respectively.

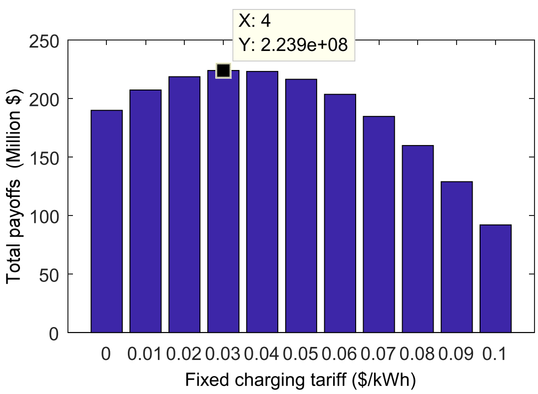

FIGURE 10. Aggregator's payoffs vs. β for minimum acceptable SOC limit (φ) of 50%.

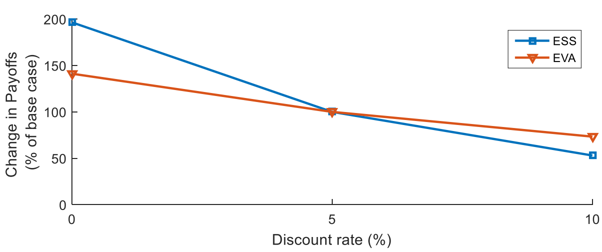

FIGURE 11. The effect of changing the discount rate of the payoffs as percentage from base case.

4) EFFECT OF CHANGING THE DISCOUNT RATE

In this section, the effect of changing the discount rate is studied. Three different discount rates are examined: 0%, 5% (base case), and 10%. Figure 11 shows the change in total payoffs (as a percentage of base case payoffs) due to the change in discount rate for the EVA and corresponding ESS cases. These results demonstrate that both EVA and ESS payoffs are strongly affected by the value of discount rate. However, EVA payoffs are relatively less sensitive to the discount rate than ESS payoffs.

5) EFFECT OF UNCERTAINTIES IN PRICES AND AS SIGNALS

In this section, we consider the effect of $\pm 10\%$ uncertainty in energy and AS prices ($\sigma^D, \sigma^U, \sigma^R, \sigma^E$) and AS signal ($\alpha^D, \alpha^U, \alpha^R$). Two cases are studied:

1. The worst-case scenario, where the AS prices are less than expected by 10%, and the AS signals and energy prices are higher by 10%.
2. The best-case scenario, where the AS prices are higher than expected by 10%, and the AS signals and energy prices are less by 10%.

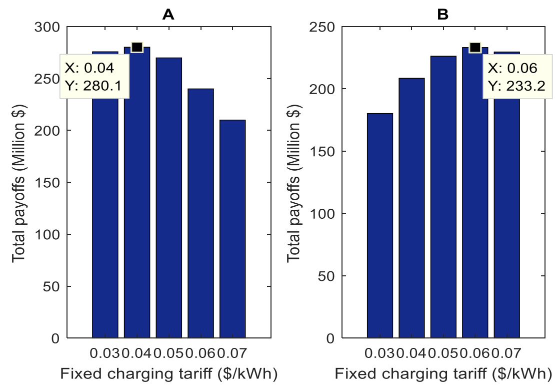

FIGURE 12. EVA payoffs vs. β for the best-case (A) and worst-case (B) scenarios.

The results of both cases are shown in figure 12. In the worst-case scenario, the results show that the optimal payoffs drop by 8.63% from \$255 million to \$233 million. The optimal tariff β is increased from 0.05\$/kWh in the base case to 0.06 \$/kWh. This increase reflects the fact that the EVA will try to attract less EVs (3500 less than the base case) due to the increase in the energy prices and reduction in the regulation prices and will offset this reduction by charging higher tariffs. On the other hand, in the best case scenario, the tariff β is decreased to 0.04 \$/kWh and the optimal payoffs increase by 9.8% to \$280 million by increasing EVs participation to 28000 EVs (3500 higher than the base case).

D. EFFECTS OF INCLUDING DYNAMIC SUPPORT SERVICE

This section conducts a study on including FRP as dynamic support services. This is done for the case where $\gamma_o = 0.6$, corresponding to line 3 in figure 1, and β ranging between 0.03 and 0.06. As seen in figure 13, when the DSS are

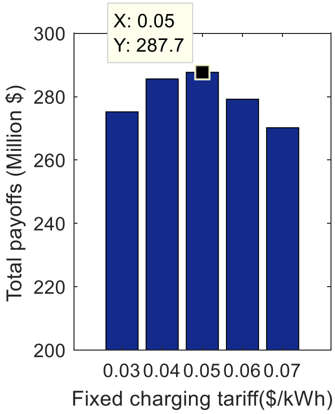

FIGURE 13. EVA payoffs vs. β when FRP is included for a max. participation of 60% $\gamma_0 = 0.6$.

TABLE 3. Comparison of investing in EV aggregators and ESS when DSS is included.

Line	Investment cost (Millions\$)	Optimal Power Capacity (MW)	Optimal Energy Capacity (MWh)	Energy Storage Payoff (Millions\$)	EV Aggregator Payoff (Millions\$)
3	41.06	172	41.5	96.6	288

included, the optimal payoffs increase by about 13% (compared with the case where those services are ignored, see figure 2). However, the results indicate that the optimal tariff has not changed, $\beta = 0.05$.

In the case of investing in ESS, including DSS yields a 140% increase in the optimal profits, as shown in Table 3. These results should be compared to those given in Table 2, where DSS are ignored. In addition, the results demonstrate that a higher power capacity is needed in this case. This is to be expected because FRP requires fast response in a short period of time. Despite the improved profitability of ESS considering FRP participation, the results indicate that EV aggregation is still the more favorable option.

VI. CONCLUSIONS

In this paper, a planning model for the market-based evaluation of two possible investment options on storage, i.e., aggregation of EV batteries and procurement of dedicated energy storage systems, is introduced. The two possible investment options are used for bidding ancillary services and dynamic support services in electricity markets. The proposed model considers the planning and operation aspects of both cases. The analyzed comparisons are based on selecting the option with the highest payoffs over the same initial investment costs, lifetime, and discount rate in both cases.

The results show that the EVA investment can be more profitable than investing in ESS. This is mainly due to the high energy capacity cost that must be paid as an initial investment cost in the ESS case. Sensitivity analyses examine the effects of variations of different parameters on the results of both options. It is shown that the energy capacity cost affects the ESS significantly while the minimum acceptable SOC limit has a considerable impact on EV aggregation. The effect of discount rate variations is milder in the EV aggregation case.

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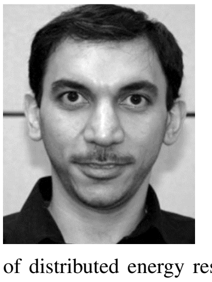

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