Demand response by load and EV aggregators enhanced by an option contract

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***Abstract*—Demand response (DR) is expected to rise with the increasing used of dynamic pricing and availability of advanced metering infrastructure in power networks. The DR capabilities will also be supplemented by the growth of electric vehicles (EV) and their aggregation in smart parking lots. EV aggregators will optimally schedule charging of the EVs depending on the varying hourly price of electricity and it will sell excess stored power to load centers. In this paper we consider a scenario having a load aggregator that schedules a large number of load consuming entities (LCEs) and an EV aggregator that manages a large fleet of parked cars. The aggregators engage in DR and mutually benefit by sharing power through option contracts at times during the day when market price peaks. We develop Nash bargaining strategies for fixed call and swing call options. A numerical problem formulated with PJM market data is used to examine the impacts of option price, strike price, and option quantity on the Nash bargaining solutions under various market power scenarios of the two aggregators.**

Keywords: option contract; energy sharing; Nash bargaining solution; demand response.

I. Introduction

Electric power networks continue to experience significant hourly variations in demand and the resulting price spikes. According to Energy Online[1], in the month of May 2018, in the ERCOT market, the price of electricity at several time instances rose to \$750 to \$1600/MWh from an average level of \$25 to \$60/MWh. The NYSO market, during the same period, experienced price spikes in the range of -\$600 to \$1000/MWh. Demand response (DR) has long been recognized as a necessity to ease demand and price spikes in power networks [5]. Recent papers and reports have also emphasized the need for network wide demand response [8, 10]. The state of DR, however, has remained limited to implementations of direct and indirect load control, guided by either direct incentives or price variations [27]. This limited state is primarily attributed to the lack of adoption of dynamic pricing (where binding prices are declared by the system operator ahead of consumption in small time intervals) and unavailability of enabling technology (advanced metering infrastructure and network connectivity of the loads). Attaining a desired level of DR will also require coordination among the large numbers of load consuming entities (LCE) in localized regions. Aggregators managing such coordination will make the DR decisions based on the dynamic price signals and the preferences of the participating LCEs.

Impending growth of electric vehicles (EVs) will soon add a new dimension to this challenge. It is estimated that the number of EVs in the U.S. will grow to 7.3 million by 2023 [4]. Considering an average battery capacity of 70 kWh, charging of these batteries even once a day may consume up to an additional 500,000 MWh. If not managed well, this may lead to further increase in price spikes. However, it is possible that EV growth can be turned into an opportunity by using smart, connected, and aggregator managed EV parking lots as the new demand response providers. Since a large number EVs in these lots will remain parked long enough, the aggregators can optimally schedule charging based on dynamically varying prices and owner preferences. This will facilitate load balancing and minimize any additional stress on the network. Moreover, the EV batteries will enable the aggregators to store extra energy and sell it to either the system operator (SO) or to other third parties during peak demand hours of the day. This paper present models for developing DR actions by residential/business loads aggregators (referred to as DRAs) and also by the EV aggregators (EVAs). The DR models are then used to design an option contract that allows a DRA to buy energy stored by an EVA during times of the day when the gap between the forward and real time prices are high.

The LCEs managed by the DRA are assumed to have fixed and deferrable (shiftable and adjustable) loads with preferred operating time windows and power levels. It is considered that all LCEs must be scheduled before the end of the day. The EVA manages an heterogeneous fleet of EVs, with different battery sizes, arrival and departure times, along with technical constraints such as maximum and minimum state of charge and maximum rates of charge/discharge. The EVA's revenue comprises the payments it receives from both the EV owners (per fixed contract) and the DRA (from the option contract). The EVA pays overcharge and undercharge penalties to the EV owners for any deviation form the desired state of charge at the time of departure from the parking lot. A dynamic pricing policy is assumed to be in place for network. The DRA and the EVA are offered binding hourly dynamic prices of electricity at each node by the system operator. These prices are considered as exogenous input to our separate DR optimization models for the DRA and the EVA for both plain and swing option contracts. These DR models are used to formulate a Nash bargaining model that yields the optimal parameters for the option contracts for load sharing between the DRA and EVA. In summary, the modeling framework allows the DRA to benefit from its ability to alter load pattern as well as buying stored energy from the EVA during peak price hours. The

[1]https://www.energyonline.co.nz (last accessed Aug 15, 2018)

EVA derives its benefits from optimal charging of the EVs as well as the temporal arbitrage opportunity. The SO benefits from the load balancing as well as the reduction of the cost to consumers.

Integration of EVs in power networks has become a critical research issue. The EVA can be seen as a mid-size source of generation or load depending on the supply-demand-price status of a network. Several studies have examined the technical and economical feasibility of incorporating EV aggregators as a network resource. A conceptual regulatory framework and a business model to integrate EVs in the network and in turn support the power system operation is proposed in [21]. A model for charging of EVs considering the non-linear state-of-charge curve for the batteries is developed in [11]. The study in [6] argues the benefits of having a profit seeking aggregator providing energy storage (e.g., using EVs in parking lots). They use a Nash bargaining model to predict the cooperative equilibrium between the aggregator and the storage providers. Aggregation and optimal charging of EVs in coordination with the SO is studied in [18]. They show the EV penetration level that a network would be able to absorb without requiring generation expansion when the charging of the EVs is coordinated with the SO. The profitability of the aggregator and the benefits to SO by offering power stored in EVs to the energy and reserve markets are explored in [22]. Optimal and risk averse bidding strategies for EV aggregators under the constraints of market uncertainty, EV owners' behavior, and aggregators' profit volatility are presented in [13, 25, 28]. In [3], a stochastic programming methodology is developed with an objective of maximizing aggregator profit by charging the EVs on low price periods under varying market prices. A stochastic model from the system operator's perspective in [16] incorporates demand response offered by the EVs. It is shown that, by using the model, SO can minimize the operation cost by optimally scheduling conventional generators, and the aggregators can minimize the electricity payment through DR participation. The objective of minimizing the cost of EV parking lot operation is approached via a cooperative game model in [1].

Option contracts in power markets have served as an effective tool to limit the risk of price uncertainty. A review of a variety of financial instruments that are used in the electricity market are discussed in [7]. Since our focus in this paper is on option contracts, we limit our review on the use of this particular instrument in power markets. The effect of choice of option parameters in the day-ahead market is studied for put options in [26]. It has been shown through a simulation study, that producers that participate in both the option and day-ahead markets get a higher share of the profit than those who only participate in the day-ahead market. In [17], the performance of American put options in the Turkish power system is compared with forward contracts. A tutorial is offered in [19], in which a multi-stage stochastic model is proposed to determine optimal option and forward contracts for a risk-averse producer. It is shown how option contracts can be used to reduce price and availability risks. Use of financial engineering methodologies to estimate the value of three common demand-response services: load curtailment, load shifting or displacement, and short-term fuel substitution is presented in [24].

In the remainder of this paper, Section II presents the mixed integer linear programs to attain optimal DR actions for DRA and EVA for both plain and swing option contracts. In Section III, the Nash bargaining solution (NBS) model is presented and its solution approach is discussed. A case study based on recent PJM market data is examined in Section IV. Section V presents the concluding remarks.

II. DR models for DRA and EVA with option contracts

In this section, we develop separate DR models for DRA and EVA considering two different types of possible option contracts between them: plain call option and swing call option.

A. Plain call option

In plain call option, the DRA holds the right, not the obligation, to acquire a fixed amount of energy, all at once, from EVA at a prespecified strike price within a given time window. The DRA pays a fee (option value) to the seller for the right.

1) DRA's DR model for plain option: We consider that the loads managed by the DRA are of two types: fixed and deferrable loads. Schedules of fixed loads are not controlled by the DRA and must be satisfied as is at each time period. The schedules and consumption level of deferrable loads are controlled by the DRA. Deferrable loads have two subcategories: shiftable loads and adjustable loads. DRA can schedule operation of shiftable loads at any time within the respective time windows. Whereas, for adjustable loads, DRA can both schedule as well as adjust the level of power consumption, while satisfying the total power requirement of the load in the operational time window.

For each LCE $i \in \mathcal{C}$, where $\mathcal{C}$ is the set of all LCEs managed by the DRA, has a set of shiftable loads denoted by $\mathcal{S}_i$, which comprises the individual loads j with consumption level s_{ij} per unit time. The length of operation of a shiftable load is denoted by τ_{ij}. The start and finish time intervals, within which the operation can be scheduled, are denoted by $\underline{T_j}, \overline{T_j} \in \mathcal{T}$, where $\mathcal{T}$ denotes the set of all time intervals of a day, over which the DRA schedules the loads. Let x_{ijt} denote a binary variable indicating on/off status of the shiftable load (i,j) during time interval $t \in \mathcal{T}$. Then, we can write:

$$\sum_{t=\underline{T_j}}^{\overline{T_j}} x_{ijt} = \tau_{ij}, \qquad \forall i \in \mathcal{C},\ \forall j \in \mathcal{S}_i. \tag{1}$$

The set of adjustable loads within a LCE is denoted by $\mathcal{A}_i$. The maximum (minimum) level of consumption per unit time of individual loads $j \in \mathcal{A}_i$ is denoted by $\overline{R_{ij}}$ ($\underline{R_{ij}}$) within the allowable interval $[\underline{R_j}, \overline{R_j}]$. Let y_{ijt} be a binary variable indicating on/off status of the adjustable load (i,j), r_{ijt} denote its energy consumption level at time interval $t \in \mathcal{T}$, and σ_{ij} denote the total required energy consumption. Then,

$$\underline{R_{ij}}\, y_{ijt} \le r_{ijt} \le \overline{R_{ij}} y_{ijt}, \quad \forall i \in \mathcal{C},\ \forall j \in \mathcal{A}_i,\ \forall t \in \mathcal{T}, \tag{2}$$

$$\sum_{t=\underline{R_j}}^{\overline{R_j}} r_{ijt} = \sigma_{ij}, \qquad \forall i \in \mathcal{C},\ \forall j \in \mathcal{A}_i. \tag{3}$$

Let $\mathcal{F}_i$ be the set of fixed loads and $f_{ijt} \in \mathcal{F}_i$ be the j^{th} fixed load of LCE i at time interval t. Then, the total energy that LCE i consumes at a given time interval t is:

$$d_{it} = \sum_{j\in\mathcal{F}_i} f_{ijt} + \sum_{j\in\mathcal{S}_i} s_{ij}x_{ijt} + \sum_{j\in\mathcal{A}_i} r_{ijt}, \quad \forall t \in \mathcal{T},\ i \in \mathcal{C}. \tag{4}$$

Thus, the energy that the DRA must buy from the grid at a give time period is:

$$d_t = \begin{cases} \sum_{i\in\mathcal{C}} d_{it} - q_t, & t_s \le t \le t_e, \\ \sum_{i\in\mathcal{C}} d_{it}, & \text{Otherwise}, \end{cases} \tag{5}$$

where q_t is the energy bought form the EVA at time interval t within the option window defined by time intervals t_s and t_e. Recall that a plain call option can only be exercised once, and the DRA has the right, but not the obligation, to exercise. Hence, we need to add the following constraints. Let $z_t = 1$, if energy is purchased by the DRA from the EVA during the time interval t and 0 otherwise, and Q is the option quantity. Then we can write that

$$\sum_{t=t_s}^{t_e} z_t \le 1, \text{ and } q_t = Qz_t, \qquad \forall t_s \le t \le t_e. \tag{6}$$

Let Π_t, K and V be the market price of electricity, the option strike price, and the option value (paid once a day) respectively. The DRA aims to minimize the total cost of its LCEs using the model below.

$$\begin{aligned} & u^{\mathsf{DRA}}(K, V, Q, \mathbf{\Pi}) = \\ & \min \sum_{t\in\mathcal{T}} \Pi_t d_t + \sum_{t=t_s}^{t_e} K q_t + V, && (7) \\ & \text{s.t., (1)–(6)}, \\ & \quad d_t, d_{it}, q_t, r_{ijt} \ge 0, \quad \forall t \in \mathcal{T},\ \forall i \in \mathcal{C}, \forall j \in \mathcal{A}_i, && (8) \\ & \quad x_{ijt} \in \{0,1\}, \qquad \forall t \in \mathcal{T},\ \forall i \in \mathcal{C}, \forall j \in \mathcal{S}_i, && (9) \\ & \quad y_{ijt} \in \{0,1\}, \qquad \forall t \in \mathcal{T},\ \forall i \in \mathcal{C}, \forall j \in \mathcal{A}_i, && (10) \\ & \quad z_t \in \{0,1\}, \qquad \forall t \in \mathcal{T}. && (11) \end{aligned}$$

2) EVA's DR model for plain option: Let $\mathcal{B}$ denote the set of EV batteries managed by the EVA. For a given time interval $t \in \mathcal{T}$, energy balance of the battery $b \in \mathcal{B}$ can be written as:

$$\phi_b s_{bt} = \phi_b s_{b,t-1} + p^+_{bt} - p^-_{bt}, \qquad \forall t \in \mathcal{T},\ \forall b \in \mathcal{B}, \tag{12}$$

where ϕ_b is the maximum capacity of the battery b, $s_{bt} \in (0,1)$ is the state of charge of battery b at the end of time interval t, p^+_{bt} is the amount of energy that the b^{th} battery draws from the grid at time interval t, and p^-_{bt} is the amount of energy that is extracted from battery b at time interval t. We assume that, the state of charge of EV batteries are not allowed to be 0 nor 1, and hence the following constraint is added to the model.

$$\underline{S_{bt}} \le s_{bt} \le \overline{S_{bt}}, \forall t \in \mathcal{T},\ \forall b \in \mathcal{B},\ 0 < \underline{S_{bt}} \le \overline{S_{bt}} < 1. \tag{13}$$

Furthermore, the charging (discharging) rate of a battery have a technical upper bound, which in general is a convex and monotonically decreasing (increasing) function of the current state of charge. For simplicity, we assume the bounds to be constant. Hence, we can write that

$$0 \le p^+_{bt} \le P^+ w^+_{bt} \qquad \forall t \in \mathcal{T},\ \forall b \in \mathcal{B}, \text{ and} \tag{14}$$

$$0 \le p^-_{bt} \le P^- w^-_{bt}, \qquad \forall t \in \mathcal{T},\ \forall b \in \mathcal{B}, \tag{15}$$

where P^+ (P^-) is the charging (discharging) upper bound, and w^+_{bt} (w^-_{bt}) is 1 if battery b is charging (discharging) at time interval t, and 0 otherwise. The next constraint guarantees that the battery b is not in charging and discharging simultaneously during time interval t:

$$w^+_{bt} + w^-_{bt} \le \omega_{bt}, \qquad \forall t \in \mathcal{T},\ \forall b \in \mathcal{B}, \tag{16}$$

where ω_{bt} is a binary parameter with the value of 1 if the b^{th} battery is connected, i.e., the EV is in the parking lot, and 0 otherwise.

We assume that the EVA charges a flat price g (¢$/kWh$) to the EV owners for charging the batteries. Hence, EV owners pay $g(s_{bT_b} - s_{b0})\phi_b$ to the EVA each time they use the parking lot, where s_{b0} is the initial state of charge of the b^{th} EV, $T_b \in \mathcal{T}$ is the departure time of the b^{th} EV, and ϕ_b is the battery rated capacity. We denote the minimum required state of charge at the time of departure of the b^{th} EV as δ_{bT_b}. Similarly, we denote the desired state of charge at the time of departure from the parking lot as ρ_{bT_b}. If the state of charge at the time of departure is above ρ_{bT_b}, the surplus energy is priced by EVA at a lower rate, which we will assume is equal to the average night time price. Let μ_1 denote the difference between the flat rate g and the average night time rate. The EVA also pays the EV owner an undercharge penalty μ_2 (¢$/kWh$) for each unit of energy below ρ_{bT_b} at the time of departure. To calculate the undercharge and overcharge fees, we introduce two continuous variables as follows:

$$s_{bT_b} - \rho_{bT_b} = s^1_b - s^2_b \qquad \forall b \in \mathcal{B}, \tag{17}$$

where $s^1_b, s^2_b \ge 0$. Then the total overcharge and under-charge fees paid by the are computed as $\mu_1 \sum_{b\in\mathcal{B}} \phi_b s^1_b$ and $\mu_2 \sum_{b\in\mathcal{B}} \phi_b s^2_b$, respectively. The following constraint is introduced to account for the power that the EVA must sell to the DRA in the option window:

$$\sum_{b\in\mathcal{B}} p^-_{bt} = \tilde{q}_t(\mathbf{\Pi}, K), \qquad t_s \le t \le t_e. \tag{18}$$

The option quantity must be supplied using the stored power if the option is exercised. However, the EVA does not know the decision making process of the DRA, therefore it must estimate q_t. We denote as estimate of the vector $\boldsymbol{q}$ given the random price of electricity $\mathbf{\Pi}$ as $\tilde{\boldsymbol{q}}(\mathbf{\Pi}, K)$, or in component-wise form, $\tilde{q}_t(\mathbf{\Pi}, K)$. Hence the EVA's DR problem for the plain option is formulated as a bi-level model as follows, where the lower level is used to obtain $\tilde{\boldsymbol{q}}(\boldsymbol{\Pi}, K)$.

$$
\begin{aligned}
& u^{\mathsf{EVA}}(K, V, Q, \boldsymbol{\Pi}) = \\
& \min \sum_{t\in\mathcal{T}}\sum_{b\in\mathcal{B}} \Pi_t p_{bt}^{+} + \mu_1 \sum_{b\in\mathcal{B}} \phi_b s_b^1 + \mu_2 \sum_{b\in\mathcal{B}} \phi_b s_b^2 \\
& \qquad - g(s_{bT_b} - s_{b0})\phi_b - K \sum_{t=t_s}^{t_e} \tilde{q}_t(\boldsymbol{\Pi}, K) - V, \qquad (19)
\end{aligned}
$$

s.t., (12)–(18),

$$p_{bt}^{+}, p_{bt}^{-}, s_{bt}, s_b^1, s_b^2 \geq 0, \qquad \forall t \in \mathcal{T},\ \forall b \in \mathcal{B}, \qquad (20)$$

$$w_{bt}^{+}, w_{bt}^{-} \in \{0, 1\}, \qquad \forall t \in \mathcal{T},\ \forall b \in \mathcal{B}, \qquad (21)$$

where

$$\tilde{q}_t(\boldsymbol{\Pi}, K) = Q\tilde{z}_t(\boldsymbol{\Pi}, K), \quad t_s \leq t \leq t_e, \qquad (22)$$

$$\tilde{\boldsymbol{z}}(\boldsymbol{\Pi}, K) = \arg\max_{\tilde{\boldsymbol{z}}} \sum_{t=t_s}^{t_e} (\Pi_t - K)\tilde{z}_t, \qquad (23)$$

$$\text{s.t., } \sum_{t=t_s}^{t_e} \tilde{z}_t \leq 1, \qquad (24)$$

$$\tilde{z}_t \in \{0, 1\}, \quad t_s \leq t \leq t_e. \qquad (25)$$

For simplicity of notation, we define $\boldsymbol{C} = (K, V, Q)$ for the plain option, and write the disutility functions as $u^{\mathsf{DRA}}(\boldsymbol{C}, \boldsymbol{\Pi})$ and $u^{\mathsf{EVA}}(\boldsymbol{C}, \boldsymbol{\Pi})$. Note that these disutilities are random variables.

B. Swing call option

Swing call option for electricity, as considered here, differs from our plain call option in the following manner: contract quantity can be purchased at one or more time instances within the window; individual purchase quantities are bounded by time dependent values; the strike price may either be fixed or vary with time; the ramp up/down rates of quantity purchased may also be bounded.

1) DRA's DR model for swing option: In addition to constraints (1)–(5) and (8)–(11) in the DRA's model for plain option, we need a few other constraints as described below. In a swing contract, if the holder exercises the option, the energy bought at each interval as well as the total quantity bought over the contract window must satisfy

$$\underline{Q_t} z_t \leq q_t \leq \overline{Q_t} z_t, \quad t_s \leq t \leq t_e, \text{ and} \qquad (26)$$

$$\underline{Q}\, z \leq \sum_{t=t_s}^{t_e} q_t \leq \overline{Q}\, z, \qquad (27)$$

where $\underline{Q_t}(\overline{Q_t})$ and $\underline{Q}(\overline{Q})$ are the lower (upper) bounds for energy purchase during a time interval t and over the total contract window, respectively. Also, $z_t = 1$ if the option is exercised at time interval t and 0 otherwise, and $z = 1$ if the option is exercised at least once within the window. Therefore the relationship between z_t and z is given as

$$\sum_{t=t_s}^{t_e} z_t \leq (t_e - t_s + 1)z. \qquad (28)$$

Then the DRA model for a swing call option can be given as

$$
\begin{aligned}
& u^{\mathsf{DRA}}(K, V, \underline{Q_t}, \overline{Q_t}, \underline{Q}, \overline{Q}, \boldsymbol{\Pi}) = \\
& \quad \min \sum_{t\in\mathcal{T}} \Pi_t d_t + \sum_{t=t_s}^{t_e} K q_t + V, \qquad (29) \\
& \quad \text{s.t., } (1)-(5), (8)-(11), (26)-(28), z \in \{0, 1\}. \qquad (30)
\end{aligned}
$$

2) EVA's DR model for swing option: Since the EVA is subjected to the value of q_t chosen by the DRA, the same general model proposed for plain option in (19) applies for the upper level problem in a swing contract. However, the lower level must consider the new contract parameters. Then we have that

$$
\begin{aligned}
& u^{\mathsf{EVA}}(K, V, \underline{Q_t}, \overline{Q_t}, \underline{Q}, \overline{Q}, \boldsymbol{\Pi}) = \\
& \quad \min \sum_{t\in\mathcal{T}}\sum_{b\in\mathcal{B}} \Pi_t p_{bt}^{+} + \mu_1 \sum_{b\in\mathcal{B}} \phi_b s_b^1 + \mu_2 \sum_{b\in\mathcal{B}} \phi_b s_b^2 \\
& \qquad - g(s_{bT_b} - s_{b0})\phi_b - K \sum_{t=t_s}^{t_e} \tilde{q}_t(\boldsymbol{\Pi}, K) - V, \qquad (31) \\
& \quad \text{s.t., } (12)\text{–}(18), (20), (21),
\end{aligned}
$$

where

$$\tilde{\boldsymbol{q}}(\boldsymbol{\Pi}, K) =$$

$$\arg\max_{\tilde{\boldsymbol{q}}} \sum_{t=t_s}^{t_e} (\Pi_t - K)\tilde{q}_t, \qquad (32)$$

$$\text{s.t., } \underline{Q_t}\tilde{z}_t \leq \tilde{q}_t \leq \overline{Q_t}\tilde{z}_t, \quad t_s \leq t \leq t_e, \qquad (33)$$

$$\underline{Q}\, \tilde{z} \leq \sum_{t=t_s}^{t_e} \tilde{q}_t \leq \overline{Q}\, \tilde{z}, \qquad (34)$$

$$\sum_{t=t_s}^{t_e} \tilde{z}_t \leq (t_e - t_s + 1)\tilde{z}, \qquad (35)$$

$$\tilde{z}_t \in \{0, 1\} \quad t_s \leq t \leq t_e, \qquad (36)$$

$$\tilde{z} \in \{0, 1\}. \qquad (37)$$

For simplicity of notation, we define $\boldsymbol{C'} = (K, V, \underline{Q_t}, \overline{Q_t}, \underline{Q}, \overline{Q})$ for the swing option, and write the disutility functions as $u^{\mathsf{DRA}}(\boldsymbol{C'}, \boldsymbol{\Pi})$ and $u^{\mathsf{EVA}}(\boldsymbol{C'}, \boldsymbol{\Pi})$.

III. Option contract design

In this section we present the model to obtain the optimal strike price and option value when all the other option parameters are given for the plain and swing option contracts. We use the Nash's approach to the bargaining problem to find a fair option contract for both DRA and EVA while considering their relative market power. Sequential Monte Carlo simulation approach is used to estimate the expected cost/revenue of the DRA and EVA.

A. Nash bargaining approach

The goal of both DRA and EVA is to minimize their disutility by establishing an optimal option contract. However, since they have conflicting objective functions, a solution that simultaneously minimizes both or their costs does not exist.

In such a scenario, the aggregators may cooperatively bargain with each other to find the most appropriate contract. The bargaining problem of the cooperative game theory [29] can be formalized as follows . Let $n = 1, 2, ..., N$ be the set of players, and S be a closed and convex subset of $\mathbb{R}^N$ to represent the set of feasible payoff (cost) allocations that the players can get if they cooperate. Let u_0^k denote the minimal (maximal) payoff (cost) that the k^{th} player would expect without cooperation. The vector (S,$u_0^1, ..., u_0^N$) is called a N-person bargaining problem. We chose the Nash bargaining solution (NBS) to address the two person (DRA and EVA) bargaining problem. NBS is known to be invariant, Pareto optimal, independent of irrelevant alternatives, and symmetrical. Furthermore, in a bilateral negotiation, it is reasonable to expect that the player with higher market power will have a larger share of the benefits than the weaker player. To incorporate the market power, we use the generalized Nash bargaining solution (GNBS) approach [14]. The GNBS for the plain option contract can be formulated as:

$$\begin{aligned} \max \ & \Big(\mathbb{E}[u^{\mathsf{DRA}}(\mathbf{0},\mathbf{\Pi})] - \mathbb{E}[u^{\mathsf{DRA}}(\boldsymbol{C},\mathbf{\Pi})]\Big)^{\alpha} \\ & \qquad \Big(\mathbb{E}[u^{\mathsf{EVA}}(\mathbf{0},\mathbf{\Pi})] - \mathbb{E}[u^{\mathsf{EVA}}(\boldsymbol{C},\mathbf{\Pi})]\Big)^{1-\alpha} \\ \text{s.t.,} \ & (1) - (25), \end{aligned} \tag{38}$$

where $\alpha \in (0, 1)$ is an indicator of DRA's relative market power, and $\mathbb{E}[u^{\mathsf{DRA}}(\mathbf{0},\mathbf{\Pi})])$ is DRA's expected payoff at the disagreement point; $\mathbb{E}[u^{\mathsf{EVA}}(\mathbf{0},\mathbf{\Pi})]$ denotes the same for EVA.

The GNBS formulation for the swing option is similar to that for plain option, with the only difference being in the set of constraints that define the feasible set. It can be written as

$$\begin{aligned} \max \ & \Big(\mathbb{E}[u^{\mathsf{DRA}}(\mathbf{0},\mathbf{\Pi})] - \mathbb{E}[u^{\mathsf{DRA}}(\boldsymbol{C'},\mathbf{\Pi})]\Big)^{\alpha} \\ & \qquad \Big(\mathbb{E}[u^{\mathsf{EVA}}(\mathbf{0},\mathbf{\Pi})] - \mathbb{E}[u^{\mathsf{EVA}}(\boldsymbol{C'},\mathbf{\Pi})]\Big)^{1-\alpha} \\ \text{s.t.,} \ & (1) - (5), (8) - (11), (12)–(18), (20), (21), \\ & (26) - (28), (30), (32) - (37). \end{aligned} \tag{39}$$

Note that, $u^{\mathsf{DRA}}(\boldsymbol{C},\mathbf{\Pi})$ and $u^{\mathsf{EVA}}(\boldsymbol{C},\mathbf{\Pi})$ can be written as

$$u^{\mathsf{DRA}}(\boldsymbol{C},\mathbf{\Pi}) = u^{\mathsf{DRA}}(K, 0, Q, \mathbf{\Pi}) + V, \tag{40}$$

$$u^{\mathsf{EVA}}(\boldsymbol{C},\mathbf{\Pi}) = u^{\mathsf{EVA}}(K, 0, Q, \mathbf{\Pi}) - V. \tag{41}$$

Similar expressions can be written for the swing option.

In the rest of this section, we present an approach for obtaining the optimal values of the option parameters. For any option contract, an expression for the option value V can be found using the first and second order conditions for a given strike price K. Let, for the plain option,

$$\begin{aligned} \overline{N} =& \Big(\mathbb{E}[u^{\mathsf{DRA}}(\mathbf{0},\mathbf{\Pi})] - \mathbb{E}[u^{\mathsf{DRA}}(\boldsymbol{C},\mathbf{\Pi})]\Big)^{\alpha} \\ & \qquad \Big(\mathbb{E}[u^{\mathsf{EVA}}(\mathbf{0},\mathbf{\Pi})] - \mathbb{E}[u^{\mathsf{EVA}}(\boldsymbol{C},\mathbf{\Pi})]\Big)^{1-\alpha}. \end{aligned} \tag{42}$$

For swing option, the expression for $\overline{N}$ is same as above with $\boldsymbol{C}$ replaced by $\boldsymbol{C'}$.

Proposition 1. *For any given K and Q, the optimal option value V is given as*

$$\begin{aligned} V =& (1-\alpha)\Big(\mathbb{E}[u^{\mathsf{DRA}}(\mathbf{0},\mathbf{\Pi})] - \mathbb{E}[u^{\mathsf{DRA}}(\tilde{\boldsymbol{C}},\mathbf{\Pi})]\Big) \\ & - \alpha\Big(\mathbb{E}[u^{\mathsf{EVA}}(\mathbf{0},\mathbf{\Pi})] - \mathbb{E}[u^{\mathsf{EVA}}(\tilde{\boldsymbol{C}},\mathbf{\Pi})]\Big), \end{aligned} \tag{43}$$

where $\tilde{\boldsymbol{C}} = [K, 0, Q]$ for the plain option and $\tilde{\boldsymbol{C}} = [K, 0, \underline{Q_t}, \overline{Q_t}, \underline{Q}, \overline{Q}]$ for the swing option.

The value of V in (43) maximizes $\overline{N}$. Note that, since V does not appear in any of the constraints of the GNBS model (38) and (39), we can use the first order and the second-order conditions. Taking the logarithm of $\overline{N}$ and letting $\frac{\partial \log(\overline{N})}{\partial V} = 0$, we obtain the optimal V in (43). It can be checked that $\frac{\partial^2 \log(\overline{N})}{\partial V^2} < 0$ for all $\alpha \in (0, 1)$. Note that since V does not appears in the constraints of the DR models, the option value can be obtained by independently solving the DR models of DRA and EVA.

If both K and V are given, then the optimal solution of the generalized Nash bargaining formulation in (38) and (39) can be found by solving the DR models of the DRA and EVA individually. Clearly, since there are no common variables between the DRA's and the EVA's models when K and V are given, the optimal solution for the GNBS can be found by minimizing the cost of the aggregators independently. However, if only V is given, the optimal solution of the problem can be found by effectively exploring the possible values of K. One such approach is by the golden-section search method, in which the value of K is fixed in each iteration. Lower and upper bounds are computed by shrinking down the range of possible values, at which the optimal solution can be obtained.

As discussed above, finding optimal NBS values for the option parameters (K and V) as well as the GNBS solution, we need to calculate $\mathbb{E}[u^{\mathsf{DRA}}(\tilde{\boldsymbol{C}},\mathbf{\Pi})]\Big)$ and $\mathbb{E}[u^{\mathsf{EVA}}(\tilde{\boldsymbol{C}},\mathbf{\Pi})]\Big)$. We use sequential Monte Carlo simulations to estimate these expected values. In this method iterative approach, for each iteration k, a random sample $\pi^{(k)}$ of hourly prices of a day is drawn from $\mathbf{\Pi}$. Then, we solve for the values of $u_k^{\mathsf{DRA}}(K, V, Q, \pi^{(k)})$ and $u_k^{\mathsf{EVA}}(K, V, Q, \pi^{k})$. This process is repeated for a large number of iteration N. The expected values are computed as averages, e.g.,

$$\mathbb{E}[u^{\mathsf{DRA}}(K, V, Q, \mathbf{\Pi})] \approx \frac{1}{N}\sum_{k=1}^{N} u_k^{\mathsf{DRA}}(K, V, Q, \pi^{(k)}). \tag{44}$$

Note that, by using SMCS, the stochastic problem is approximated by solving a large number of instances of a deterministic mixed integer linear problem, which is done efficiently by commercial solvers such as GUROBI and CPLEX.

IV. Computational study and results

We tested the proposed option design models by constructing a sample problem using the hourly locational marginal prices (LMPs) of electricity from July 15, 2017 to July 30, 2017 at the DAY node of the PJM market in the U.S. We use this data to construct the input for the hourly prices ($\mathbf{\Pi}$) for our model. A multinormal distribution is assumed to describe the price variations. The mean and covariance of

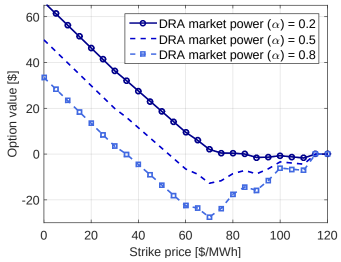

Fig. 1: Option value as a function of the strike price for different relative market power, for plain call option

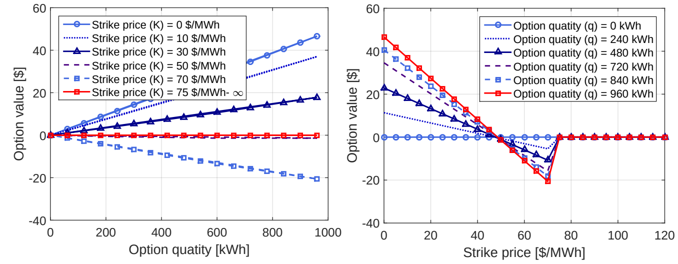

Fig. 2: Option value for different combinations of the strike price and option quantity for plain option

the distribution is obtained from the overall average and the hourly variance, respectively, of the LMPs. The load (before demand response) managed by DRA is assumed to have the same shape as the load at DAY bus. The magnitude, however, is scaled by a factor of 80. This load is categorized into fixed (40%), adjustable (30%) and shiftable (30%) loads. To keep the numerical example simple, it is considered that the total adjustable load for the day is consumed by five load consuming entities (LCEs). For each of these entities, a separate time window (hours) is allocated (3–11, 5–14, 7–14, 12–21, and 10–17) and within those hours the entities must be scheduled such that they consumer their designated amount of energy. The total shiftable load is also assumed to be consumed by five LCEs with designated time windows in hours (same as adjustable loads).

with the exception that the consumption of each entity is scheduled in only one of the hours in the respective windows.

For the sake of simplicity, we consider the following characteristics for the EVA. It manages a parking lot with a capacity to park and charge 200 EVs. Each EV battery has a rate capacity of 30 kWh. EVs arrive to the parking lot at 8 AM and depart at 6 PM.

For simplicity, we assume that all EVs arrive on average with a 50% state of charge (SOC) and have a desired SOC of 70% at the time of departure. The SOC at the time of departure can be as low as 60% and as high as 90%. The penalties for undercharge and overcharge (from the desired 70%) are same and equal to 5¢/kWh. The charging cost paid by the EV owners is 8¢/kWh. The time window for the option contract is from 3 PM to 6 PM. In the plain call option, the option quantity is 1000 kWh. For the swing call option: (1) the maximum total option quantity is 1000 kWh and (2) the upper limit of energy bought at any given time interval within the window is 250 kWh. The models are implemented using Julia-0.6.2 and GUROBI 7.5.2. The results are summarized in Figures 1 to 4.

Figure 1 shows the optimal option values (V) as a function of the strike price (K) for plain option and for various levels of DRA market power (α). The optimal option values are obtained using (43), for which the expectations are calculated over thirty different daily price realizations drawn from the multinormal distribution described earlier. This same set of price realizations are used for all optimal option values in the figure. It is observed that the option value decreases monotonically (up to a certain point) with increase in the strike price. Interestingly, the option value drops below zero, which indicates that, beyond a certain strike price (e.g., approximately \$36/MWh and α=0.8 for plain call option), the Nash bargaining solution reverses the option value payment (i.e., EVA pays to DRA) in order to make the contract feasible. For lower values DRA's relative market power, the option values become negative at higher strike prices. Beyond a certain strike price (\$70/MWh for plain call option) irrespective of the value of α, an increasing number of the price realizations fall below the strike price, not triggering the option purchase. This makes the difference between the expected utilities with and without option, see (43), smaller. This gradually pushes the value of V closer to zero as strike price continues to increase. After a certain high value of K, when all price realizations in the set are below the strike price within the time window, the option value remains at zero as there are no more gains to be made from the option contract. It is observed that the turning point for V is independent of market power, as it depends only on the strike price and the set of price realizations. A similar trend is observed for the swing call option, where the turning point for V is approximately at $K =$ \$55/MWh. This is expected, as the revenue that EVA earns from DRA is higher in plain call option than the swing option.

Figure 2 shows the option value for different combinations of K and Q. From the figure on the left, we observe the following: the option value increases with option quantity, albeit at a slower pace as the strike price increases; beyond a certain higher strike price $K =$\$70/MWh, the option value decreases with increasing quantity; with further increase in strike price (say, $K =$\$75/MWh), option value remains at zero. The figure in the right depicts Nash-bargaining combinations of option value and strike price for various option quantities. It can be observed that for a given strike price, the option value increases with the option quantity. Similarly, for a given option value, the strike price increases with quantity.

In Figure 3, the expected NBS costs of the DRA and EVA are presented for different values of K and α for plain option. The horizontal portion of the curves (i.e., for all K values up to \$55/MWh) represents option contracts, in which the price scenarios always exceed the strike price and the Nash bargaining solution yields lowest cost for both DRA and EVA. As the strike price increases beyond \$55/MWh, in some of the price scenarios the strike price is never exceeded within the time window and hence the expected cost begins to increase.

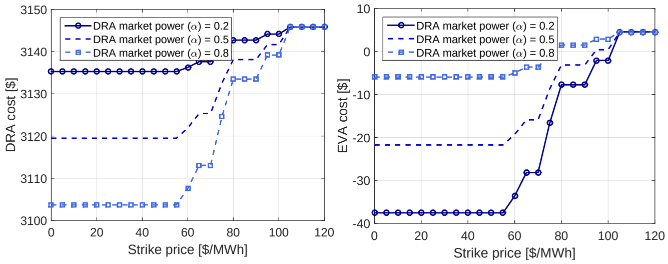

Fig. 3: DRA and EVA cost for different optimal strike prices in plain call option

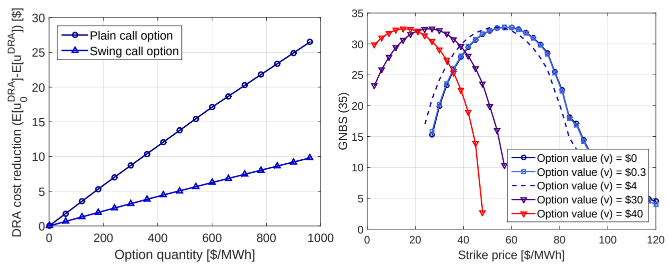

Fig. 4: Left: DRA and EVA cost reduction comparison. Right: GNBS for different option prices for plain call option

The NBS costs reach their highest values ($3145.813 for DRA and $4.5760 for EVA) and remains constant for K values $105/MWh and higher. Note that these maximum cost values correspond to the disagreement point. It is clear that for the chosen problem scenario, the EVA and DRA should select any strike price that is below the threshold of $55/MWh for maximizing their Nash bargaining benefits. We also note that the total expected profit is $52.651, which is the difference between the disagreement cost and the Nash bargaining cost for K below $55/MWh. The profit is shared such that the DRA gets $\alpha \times 100\%$ and the rest goes to EVA. Thresholds for K and the profit distribution can be obtained using our model for any other numerical variants of our problem. A similar behavior is observed for the case of swing option.

Figure 4 (left) shows the total expected NBS profit of DRA, for $K \leq 55$ and α=0.5. For increasing values of the option quantity (Q), the profit grows linearly. This pattern should hold as long as DRA has the capacity to fully consume the option quantity. If Q grows too large beyond DRA's capacity, then the plain option profit will drop to zero. However, the swing option profits may continue to grow further, depending on the nature of the contract before eventually dropping to zero. Figure 4 (right) shows the plots of the objective function of the generalized Nash bargaining (GNBS) model (for the plain option) for various combinations of the option value and strike price. It shows that the optimal Nash bargaining solution is the same for all different values V. Similar relationships are also observed for the swing call option.

V. Conclusions

Expected increase in the practice of dynamic pricing in power networks, as well as the availability of advanced metering infrastructure will expand the use of demand response by the load aggregators (DRA). A new contributor to the demand response is expected to be the EV aggregators (EVA) who will manage a growing number of smart and connected parking lots in the cities that will host large numbers of EVs for a considerable part of the day. Charging of these EVs will consume a significant amount of energy, which will be scheduled optimally by the EVA based on dynamic hourly prices and customer preferences. EVA will also store excess power in the EVs for temporal arbitrage. In this paper, we first develop demand response models for the DRA and the EVA assuming that a dynamic pricing policy is in effect. Thereafter, we show how the demand response capabilities can be enhanced through an option contract designed for DRA to buy power stored by EVA. A Nash bargaining solution approach is used in designing the parameters of the option contract. Data from an existing load node (DAY) in the PJM network is used to develop a sample numerical problem scenario. Using this numerical problem, we examine the properties of two different kinds of option contracts (plain and swing) and assess their benefits to the participating aggregators. It is demonstrated via numerical results that the temporal arbitrage through an option contract can increase demand response and reduce cost to the consumers. An expression for obtaining the optimal option value for a given strike price and quantity is developed. Numerical results show that for a given option quantity, option value always adopts to an optimal (Nash bargaining) level for any given strike price, and vice versa. Another key feature of our approach is that the solution of the Nash bargaining model uses only the outcomes of the DRA and EVA models, and thus the parties do not require sharing of their technical information (objective function and constraints). It is assumed that both DRA and EVA are loads on the same bus of the network. If they are not, congestion costs and differences in hourly prices must be considered for the option contract design.

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