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Strategic Behavior of Distributed Energy Resources in Energy and Reserves Co-optimizing Markets

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Abstract— **We consider decentralized scheduling of Distributed Energy Resources (DERs) in a day-ahead market that clears energy and reserves offered by both centralized generators and DERs. Recognizing the difficulty of scheduling transmission network connected generators together with distribution feeder connected DERs that have complex inter-temporal preferences and dynamics, we propose a tractable distributed algorithm where DERs self-schedule based on granular Distribution Locational Marginal Prices (DLMPs) derived from LMPs augmented by distribution network costs. For the resulting iterative DER self-scheduling process, we examine the opportunity of DERs to engage in strategic behavior depending on whether DERs do or do not have access to detailed distribution feeder information. Although the proposed distributed algorithm is tractable on detailed real-life network models, we utilize a simplified T&D network model to derive instructive analytical and numerical results on the impact of strategic DER behavior on social welfare loss, and the distribution of costs and benefits to various market participants.**

I. Introduction

Increasing penetration of environmentally sustainable, albeit intermittent and volatile, renewable generation can benefit from significantly positive synergies with flexible Distributed Energy Resource (DER) loads. DERs, such as electric vehicles (EVs), can schedule their hourly charging rate and provide secondary reserves. EVs self-schedule based on hourly day-ahead distribution location marginal-cost-based prices (DLMPs) determined by coordinating Independent System Operator (ISO) and Distribution System Operators (DSOs) who clear the market. DLMPs are equal to transmission locational marginal prices (LMPs) adjusted for distribution line marginal losses [1].

Unfortunately, familiar centralized market-clearing algorithms are computationally intractable due to large number of DERs connected to distribution networks, and their complex inter-temporal dynamics. Load aggregation and direct centralized utility control methods proposed in the literature in order to address these difficulties [2]–[4] as well as open-loop optimal EV charging approaches [5], [6] are not scalable for DER market integration. Distributed algorithm methods based on self-scheduling DERs adapting to system operator determined DLMPs appears the only tractable approach due to complex DER dynamics as well as associated information communication constraints [1], [7].

Two important questions arise from the need to rely on distributed DER self-dispatch: (i) Is there a unique equilibrium that can be obtained for the market to clear, and (ii) can DERs increase their individual benefits at the expense of social welfare by engaging in strategic behavior? Given the hierarchical structure of distributed algorithms, there is a vast literature on game theory approaches to market-clearing with DERs. An extensive review of game theoretical methods applied to power systems can be found in [8]. The existence and uniqueness of Nash equilibrium in daily distributed DER scheduling is shown in [9]. In [18], the equilibrium for price taking and price anticipating DERs is studied; however, salient network characteristics, such as line losses, are omitted. Single time period Nash Equilibrium in energy storage is studied in [10] and [11].

In our multi-product model where DERs trade both energy and reserves, it is the second question that constitutes this paper's contribution. The readers can refer to [12]–[17] for convergence and strategic behavior issues. This paper extends past work by investigating strategic behavior under cases of local network feeder characteristics information available to self-scheduling DERs, enabling them to impute competitor behavior. Furthermore, it discusses the feasibility of obtaining such local information and the magnitude of the associated loss of social welfare.

We are able to obtain analytical as well as extensive numerical results by (i) focusing on EVs and their salient day-ahead hourly preferences/dynamics including mobility across distribution feeders, and (ii) accurately modeling generator costs while simplifying, without loss of generality of our analytical results, the transmission and distribution (T&D) networks. Although a centralized market-clearing model with massive DERs is not tractable for real-sized problems, we formulate and solve it for small problems and use it as a benchmark for the distributed algorithm solutions. We refer to the centralized model as the *global* information problem. More importantly, analytical expressions of equilibrium optimality conditions of the global model are compared to the ones associated with the distributed algorithm decisions with or without local feeder network information.

More specifically, two information cases are considered: (i) DERs have no information about the distribution network characteristics that influence their local DLMP, hence they are pure price takers, and (ii) DERs do have access to local distribution feeder characteristics enabling them to translate marginal line loss information to an estimate of the most recent aggregate local participant consumption decision, and from it construct a functional relation of how their own decision is likely to affect their local DLMP. The main conclusion of the paper is that it is possible for self-scheduling DERs to behave strategically at the expense of social welfare,

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when they have access to network information. Moreover, the impact of DER behavior on social welfare increases with DER penetration.

The remainder of this paper is organized as follows. Section II presents a simplified model of a radial distribution network, with DERs and fixed demand connected to the end of a single line feeder, and provides a detailed formulation of the global information model. Section III introduces the centralized and distributed market clearing models with local distribution network information. Section IV compares the models, and Section V lists numerical results for a simple example. Lastly, Section VI concludes and provides directions for further research.

II. T&D Network Approximation and Global Information Model

In this section, we present a T&D network approximation in subsection II-A, and a global information model (in subsection II-B) in which the ISO has global information on the network and all market participants.

A. T&D Network Approximation

We assume a radial distribution network with N feeders, which are connected to a single transmission bus, denoted by ∞. Each feeder $n = 1, \ldots, N$ is represented by a single line connecting the T&D interface node (substation) to a single node where DERs and conventional loads are connected. We use subscript P for real power and R for reserves. Index n is used for each line $(\infty - n)$ as well as the end-node of this line, interchangeably (see Fig. 1). This abstraction greatly simplifies the notation, but does not affect the validity of our results.

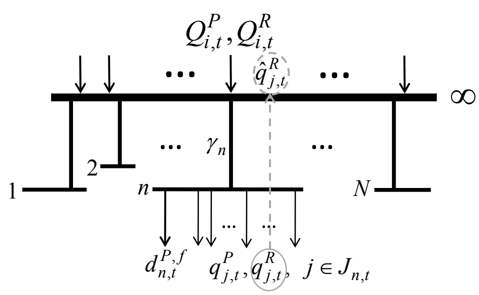

Fig. 1. T&D Network approximation.

Each line n incurs losses $l_{n,t}$ that are related to the total demand $d^P_{n,t}$ at node n using a loss factor (LF_n), as follows:

$$l_{n,t} = LF_n (d^P_{n,t})^2 = \frac{\gamma_n}{2}(d^P_{n,t})^2, \tag{1}$$

where we introduce γ_n for notational simplicity.[1] Losses $l_{n,t}$ are referred to as "quadratic" losses, as opposed to "marginal" losses, denoted by $m_{n,t}$, which are given by

$$m_{n,t} = \frac{\partial l_{n,t}}{\partial d^P_{n,t}} = \gamma_n d^P_{n,t}. \tag{2}$$

[1]Note that γ_n is defined at each node, and hence the single node approximation for each line is easily generalizable.

Conventional generators, indexed by i, are connected at the transmission bus ∞. Generator i provides at each hour t real power $Q^P_{i,t}$, and reserve $Q^R_{i,t}$, incurring an (as-bid) cost $C^P_i(Q^P_{i,t})$, and $C^P_i(Q^R_{i,t})$, which are respectively given by

$$C^P_i(Q^P_{i,t}) = \alpha^P_i (Q^P_{i,t})^2 + \beta^P_i (Q^P_{i,t})^2, \tag{3}$$

$$C^R_i(Q^R_{i,t}) = \alpha^R_i (Q^R_{i,t})^2 + \beta^R_i (Q^R_{i,t})^2. \tag{4}$$

EVs, indexed by j, are connected at the distribution nodes, with $z_{j,n,t} = 1$ if EV j is connected at node n, at time period (hour) t, and $z_{j,n,t} = 0$, otherwise (note that $\sum_n z_{j,n,t} \leq 1$, $\forall j, t$). Let J be the set of EVs, then subset $J_{n,t}$ includes EVs connected at node n, hour t ($z_{j,n,t} = 1$). Also, let T_j denote the set of hours that EV j is connected at some node ($\sum_n z_{j,n,t} = 1$). Assuming EV j visits node n once a day (daily pattern), we denote by t^{dep}_n the departure hour from node n. While connected, EV j consumes $q^P_{j,t}$ during hour t, and by the time it departs from a certain node, it must be charged by a certain minimum amount ($\underline{s}_{j,n}$) that should be sufficient for traveling. While traveling, EV j consumes $d_{j,t}$. While connected, EV j can provide reserve $q^R_{j,t}$. The provision of reserve at node n translates to a higher amount at the transmission bus ∞, due to the line losses.[2] The total demand at each node n, hour t, $d^P_{n,t}$, is the sum of inelastic (fixed) demand $d^{P,f}_{n,t}$, and the total EV consumption, i.e.,

$$d^P_{n,t} = d^{P,f}_{n,t} + \sum_{j \in J_{n,t}} q^P_{j,t} \tag{5}$$

Given that the total EV reserve provision is much smaller compared to inelastic demand, we assume that incremental losses at full reserve deployment are adequately represented by marginal losses. In this case, as illustrated in Fig. 1, EV reserve offer at the distribution node n, $q^R_{j,t}$ is translated to $\hat{q}^R_{j,t}$ at the transmission bus, as follows:

$$\hat{q}^R_{j,t} = (1 + m_{n,t}) q^R_{j,t}, \quad j \in J_{n,t}. \tag{6}$$

B. Global Information Model ($\mathbf{TD^{opt}_F}$)

Assuming that the ISO has global information on the T&D network characteristics as well as on the EV preferences/costs, we obtain the following optimization problem referred to as $\mathbf{TD^{opt}_F}$, where TD refers to simultaneously optimizing the T&D network/resources, and subscript F implies feeder information (in particular with respect to the functional form of the losses):

$$\underset{\substack{Q^P_{i,t}, Q^R_{i,t}, \\ q^P_{j,t}, q^R_{j,t}}}{\text{minimize}} \sum_{i,t} \{C^P_i(Q^P_{i,t}) + C^R_i(Q^R_{i,t})\} + \sum_{j,t} \epsilon (q^P_{j,t})^2, \tag{7}$$

subject to:

$$\sum_i Q^P_{i,t} = \sum_n (l_{n,t} + d^P_{n,t}) \quad \forall t \rightarrow \lambda^P_{\infty,t}, \tag{8}$$

[2]More precisely, the first Watt of reserves deployed at node n, provides a relief at the T&D interface bus that equals $1 + m_{n,t}$. Given that reserve deployment is generally small compared to $d^P_{n,t}$, we use the conservative approximation of incremental losses by the marginal losses $m_{n,t}$ of the first Watt of reserves offered.

$$\sum_i Q^R_{i,t} + \sum_{n,j\in J_{n,t}} (1+m_{n,t})q^R_{j,t} \geq D^R_t \quad \forall t \rightarrow \lambda^R_{\infty,t}, \quad (9)$$

$$Q^P_{i,t} + Q^R_{i,t} \leq \overline{Q}_i, \quad Q^P_{i,t} - Q^R_{i,t} \geq \underline{Q}_i \quad \forall i,t, \quad (10)$$

$$s_{j,t} = s_{j,t-1} + q^P_{j,t} - d_{j,t} \quad \forall j, t\in T_j \rightarrow \zeta^{(1)}_{j,t}, \quad (11)$$

$$q^P_{j,t} + q^R_{j,t} \leq \overline{q}^C_j \quad \forall j,t \rightarrow \zeta^{(2)}_{j,t}, \quad (12)$$

$$q^R_{j,t} \leq q^P_{j,t} \quad \forall j,t \rightarrow \zeta^{(3)}_{j,t}, \quad (13)$$

$$s_{j,t} \leq \overline{q}^P_j \quad \forall j,t, \qquad s_{j,t^{dep}_n} \geq \underline{s}_{j,n} \quad \forall j,n, \quad (14)$$

$$s_{j,0} = s^{(0)}_j, \quad \forall j, \quad (15)$$

where $C^P_i(Q^P_{i,t})$, $C^R_i(Q^R_{i,t})$ are given by (3) and (4), dependent variables $l_{n,t}$ and $m_{n,t}$ are defined in (1) and (2), $s_{j,t} \geq 0$ is a variable indicating the State of Charge (SoC) of EV j at hour t, and also $Q^P_{i,t}, Q^R_{i,t}, q^P_{j,t}, q^R_{j,t} \geq 0$, $\forall i,j,t$.

The objective function (7) minimizes the total generation and reserve provision cost plus the EV battery degradation cost, where ϵ is a degradation coefficient that penalizes fast charging due to battery health concerns [19]. The energy balance constraint (8) states that at the transmission bus, total generation must meet the demand plus line losses. Constraint (9) states the reserves provided from both generators and EVs should meet the requirements D^R_t. The dual prices of these constraints ($\lambda^P_{\infty,t}, \lambda^R_{\infty,t}$) represent the energy and reserve prices at the transmission bus, namely the LMPs. Constraints (10) represent the technical maximum ($\overline{Q}_i$) and minimum ($\underline{Q}_i$) generation constraints. Constraints (11)–(15) are EV-related: (11) represents the SoC ($s_{j,t}$) dynamics ($d_{j,t}$ is a parameter); (12) refers to the charger capacity ($\overline{q}^C_j$); (13) ensures that the battery never provides net energy to the grid, i.e., there is no instance of Vehicle to Grid power flow; (14) imposes a minimum amount of charging at the departure of an EV from a certain node and ensures that the battery capacity ($\overline{q}^P_j$) is not exceeded, and (15) initializes the SoC.

Arguably, the ISO does not have, nor is it practical to obtain detailed distribution network information. As a result, it practically has no information on the actual functional form of the losses in (1) and (2). Such information is provided and calculated (for a given load and EV consumption profile) by the DSOs that do have local knowledge of the network characteristics.

EVs provide services to the transmission market, and they may opt to communicate their preferences to the ISO while relying on their local DSO to estimate and provide line loss information to the ISO. Alternatively, in a distributed implementation, EVs do not communicate their preferences; instead they self-dispatch conditional upon tentative energy and reserve prices. More specifically, EVs are charged the energy DLMP at node n, hour t, $\lambda^P_{n,t}$ for their energy consumption $q^P_{j,t}$, and rewarded the reserve DLMP $\lambda^R_{n,t}$ for their reserve provision $q^R_{j,t}$. These spatiotemporal prices for node n, hour t are obtained by adjusting the transmission bus LMPs for the marginal losses, as follows:

$$\lambda^P_{n,t} = (1+m_{n,t})\lambda^P_{\infty,t}, \quad (16)$$

$$\lambda^R_{n,t} = (1+m_{n,t})\lambda^R_{\infty,t}. \quad (17)$$

Particularly for the reserves, we may think that reserves are paid at the reserve LMP $\lambda^R_{\infty,t}$ but for a quantity $\hat{q}^R_{j,t} = (1+m_{n,t})q^R_{j,t}$, which is equivalent to (17).

As we mentioned, the ISO cannot in practice have distribution network information —this is local information— and hence the global information model mainly serves as a benchmark. In the next section, we consider models with relying only on local information of the distribution network, under both a centralized and a distributed implementation.

III. Local Information Models

In this section, the DSOs (and not the ISO) have the local information, which includes the detailed feeder models. We present two types of models: a centralized implementation (in Subsection III-A) in which EVs communicate their preferences/cost to the ISO, and a distributed implementation (in Subsection III-B), in which EVs self-dispatch conditional upon tentative energy and reserve prices. In the distributed model, we further explore the cases in which EVs may or may not have local knowledge of feeder model details.

A. Centralized Model with Summarized Local Information ($\mathbf{TD^{opt}}$)

In this case, EVs communicate their preferences and costs to the ISO, who does not have knowledge of the detailed feeder model needed to calculate $l_{n,t}$ and $m_{n,t}$. These values are calculated and provided by the DSO. An outline of the procedure is provided below:

Step 1: EVs initially communicate their costs and preferences to the ISO. The DSO provides an estimate for the inelastic demand, and the values of line losses.

Step 2: ISO minimizes the total system cost by dispatching generators and EVs, conditional upon the information provided by the DSO, and communicates the EV schedules to the DSO.

Step 3: The DSO calculates the network losses for the new EV schedules, and provides these updated values to the ISO.

Steps 2 and 3 are repeated until convergence. Specifically, at iteration $k+1$, the ISO solves an optimization problem — referred to as $\mathbf{TD^{opt}}$, i.e., without feeder information — to obtain optimal schedules for generators and EVs, assuming fixed $m^{(k)}_{n,t}$, as they have been provided from the previous iteration k, and a first order Taylor expansion for the quadratic losses around $d^{P,(k)}_{n,t}$ in constraint (8). The following constraints replace (8) and (9):

$$\sum_i Q^P_{i,t} = \sum_n (l^{(k)}_{n,t} - m^{(k)}_{n,t} d^{P,(k)}_{n,t}) + (1+m^{(k)}_{n,t}) d^P_{n,t} \quad \forall t, \quad (18)$$

$$\sum_i Q^R_{i,t} + \sum_{n,j\in J_{n,t}} (1+m^{(k)}_{n,t}) q^R_{j,t} \geq D^R_t \quad \forall t, \quad (19)$$

where the total demand $d^{P,(k)}_{n,t}$ is updated based on EV schedules $q^{P,(k)}_{j,t}$, and this demand is used to calculate $m^{(k)}_{n,t}$, and $l^{(k)}_{n,t}$. Hence, the optimization problem ($\mathbf{TD^{opt}}$) is a Quadratic Problem (QP) defined as follows:

$\mathbf{TD^{opt}}$: (7), s.t. (18), (19), (10) – (15).

B. Distributed Models with Full/Summarized Local Information ($\mathbf{EV^{opt}}, \mathbf{EV_F^{opt}}$)

We now consider EVs that do not communicate their preferences/costs to the ISO. Instead, they self-dispatch conditional upon tentative DLMPs. More specifically, EV j solves the following optimization problem — referred to as EV-problem— to minimize its cost, i.e., the energy cost (energy charged at the DLMP) minus the benefit from reserve provision (remunerated at the reserve DLMP) plus the battery degradation cost. The EV objective function is provided below:

$$\underset{q_{j,t}^P, q_{j,t}^R}{\text{minimize}} \sum_{n,t} z_{j,n,t}(\widetilde{\lambda}_{n,t}^P q_{j,t}^P - \widetilde{\lambda}_{n,t}^R q_{j,t}^R) + \sum_t \epsilon (q_{j,t}^P)^2, \quad (20)$$

where, we denote by $\widetilde{\lambda}_{n,t}^P$ and $\widetilde{\lambda}_{n,t}^R$ the DLMPs that the EVs use to self-schedule (we will elaborate on how these values are defined and related to (16) and (17) shortly). Hence, the EV problem is as follows:

EV-problem: (20), s.t. (11) – (15).

The distributed implementation is as follows:

Step 1: The ISO broadcasts initial values of LMPs and the DSO provides initial values for the marginal losses.

Step 2: EVs obtain the ISO LMPs and DSO calculated marginal losses, synthesize DLMPs, and solve their cost minimization problem (EV-problem). They communicate their schedules to the ISO/DSO.

Step 3: The DSO updates the losses, and provides them to the ISO and the EVs.

Step 4: The ISO then clears the market with fixed EV schedules, and line losses (we refer to this problem as $\mathbf{T^{opt}}$ since it basically optimizes the transmission network). The ISO "filters" the LMPs of the $\mathbf{T^{opt}}$ solution, and announces tentative LMPs to the EVs. Steps 2-4 are repeated until convergence of the EV schedules.

In Step 4, the ISO optimization problem $\mathbf{T^{opt}}$ for iteration k differs from $\mathbf{TD^{opt}}$ as follows:

$$\underset{Q_{i,t}^P, Q_{i,t}^R}{\text{minimize}} \sum_{i,t} \{C_i^P(Q_{i,t}^P) + C_i^R(Q_{i,t}^R)\} \quad (21)$$

subject to:

$$\sum_i Q_{i,t}^P = \sum_n (l_{n,t}^{(k)} + d_{n,t}^{P,(k)}) \quad \forall t \to \lambda_{\infty,t}^P \quad (22)$$

$$\sum_i Q_{i,t}^R + \sum_{n,j \in J_{n,t}} (1 + m_{n,t}^{(k)}) q_{j,t}^{R,(k)} \geq D_t^R \ \forall t \to \lambda_{\infty,t}^R \quad (23)$$

where $d_{n,t}^{P,(k)}$ is calculated using (5), for given $q_{j,t}^{P,(k)}$. Hence, $\mathbf{T^{opt}}$ is also a QP problem listed below for clarity:

$\mathbf{T^{opt}}$: (21), s.t. (22), (23), (10).

Following the solution of $\mathbf{T^{opt}}$, the ISO filters the dual prices (LMPs) $\lambda_{\infty,t}^{P,(k)}, \lambda_{\infty,t}^{R,(k)}$, and broadcasts $\widetilde{\lambda}_{\infty,t}^{P,(k)}$ and $\widetilde{\lambda}_{\infty,t}^{R,(k)}$ as follows:

$$\widetilde{\lambda}_{\infty,t}^{P,(k)} = \widetilde{\lambda}_{\infty,t}^{P,(k-1)} + \rho_t^{P,(k)}(\lambda_{\infty,t}^{P,(k)} - \widetilde{\lambda}_{\infty,t}^{P,(k-1)}), \quad (24)$$

$$\widetilde{\lambda}_{\infty,t}^{R,(k)} = \widetilde{\lambda}_{\infty,t}^{R,(k-1)} + \rho_t^{R,(k)}(\lambda_{\infty,t}^{R,(k)} - \widetilde{\lambda}_{\infty,t}^{R,(k-1)}), \quad (25)$$

where $\rho_t^{R,(k)}$ is a direction-dependent stepsize defined by

$$\rho_t^{P,(k)} = \begin{cases} \min\{\rho_0^P, \underline{u}\rho_t^{P,(k-1)}\} & \text{if } \Delta\lambda_t^{P,(k)} \Delta\lambda_t^{P,(k-1)} < 0 \\ \min\{\rho_0^P, \overline{u}\rho_t^{P,(k-1)}\} & \text{otherwise,} \end{cases} \quad (26)$$

where $\Delta\lambda_t^{P,(k)} = (\widetilde{\lambda}_{\infty,t}^{P,(k-1)} - \lambda_{\infty,t}^{P,(k)})$, and $\underline{u} < 1$, $\overline{u} > 1$ are constants, and ρ_0^P is the nominal stepsize value, which is also its upper bound. Therefore, the value of the stepsize is decreased if there is a sign change in $\Delta\lambda_t^{P,(k)}$ compared to $\Delta\lambda_t^{P,(k-1)}$, otherwise it is increased.

In what follows, we elaborate on the EV problem of Step 2, and consider two cases.

1) EVs without Feeder Information ($\mathbf{EV^{opt}}$): In this case, EVs do not have information on the functional form of $m_{n,t}$ that affect the DLMPs. Hence, EVs are price takers and their optimal strategy is dependent on $[\widetilde{\lambda}_{n,t}^P, \widetilde{\lambda}_{n,t}^R]$. These are parameters in the EV-problem, obtained by the ISO-broadcasted tentative LMPs, $\widetilde{\lambda}_{\infty,t}^P$ and $\widetilde{\lambda}_{\infty,t}^R$, and the DSO calculated marginal losses $m_{n,t}$. At iteration k, the objective function of the EV problem becomes:

$$\underset{q_{j,t}^P, q_{j,t}^R}{\text{minimize}} \sum_{n,t} z_{j,n,t} \widetilde{\lambda}_{\infty,t}^{P,(k-1)} (1 + m_{n,t}^{(k-1)}) q_{j,t}^P - \sum_{n,t} z_{j,n,t} \widetilde{\lambda}_{\infty,t}^{R,(k-1)} (1 + m_{n,t}^{(k-1)}) q_{j,t}^R + \sum_t \epsilon (q_{j,t}^P)^2 \quad (27)$$

For clarity, we denote this problem as $\mathbf{EV^{opt}}$, i.e.,

$\mathbf{EV^{opt}}$: (27), s.t. (11) – (15).

2) EVs with Feeder Information ($\mathbf{EV_F^{opt}}$): In this case, EVs have local network knowledge, hence they have information on the functional form of $m_{n,t}$ of their feeder. Therefore, given the value of $m_{n,t}$, EV j, $j \in J_{n,t}$, can infer the value of residual load at node n, hour t, where the residual load is the sum of inelastic demand $d_{n,t}^{P,f}$ and $q_{-j,t}^P = \sum_{j' | j' \neq j, j' \in J_{n,t}} q_{j',t}^P$. At iteration k, EV j using the value $m_{n,t}^{(k-1)}$, and assuming that other EVs will remain fixed to their previous schedules, has information on how his schedule can affect the marginal losses, and hence the DLMPs. The DLMPs $\widetilde{\lambda}_{n,t}^P$, and $\widetilde{\lambda}_{n,t}^R$ are no longer parameters in the optimization problem, but a function of the marginal losses, which has the following form:

$$m_{n,t}(q_{j,t}^P) = \gamma_n (q_{j,t}^P + q_{-j,t}^{P,(k-1)} + d_{n,t}^{P,f}) \quad (28)$$

Hence, the objective function of EV j in this case becomes

$$\underset{q_{j,t}^P, q_{j,t}^R}{\text{minimize}} \sum_{n,t} z_{j,n,t} \widetilde{\lambda}_{\infty,t}^{P,(k-1)} [1 + m_{n,t}(q_{j,t}^P)] q_{j,t}^P - \sum_{n,t} z_{j,n,t} \widetilde{\lambda}_{\infty,t}^{R,(k-1)} [1 + m_{n,t}(q_{j,t}^P)] q_{j,t}^R + \sum_t \epsilon (q_{j,t}^P)^2 \quad (29)$$

For clarity, we denote this problem as $\mathbf{EV_F^{opt}}$, i.e.,

$\mathbf{EV_F^{opt}}$: (29), s.t. (11) – (15).

IV. Model Comparison

In this section, we compare the first order optimality conditions for each of the above models, and we identify the differences which we call "mismatch terms."

The derivative of the Lagrangian with respect to EV consumption $q_{j,t}^P$, for the global model $\mathbf{TD_F^{opt}}$ is:

$$\lambda_{\infty,t}^P \sum_n z_{j,n,t}(1+m_{n,t}) - \lambda_{\infty,t}^R \sum_n z_{j,n,t}\gamma_n \sum_{j\in J_{n,t}} q_{j,t}^R + A = 0, \quad (30)$$

where $A = 2\epsilon q_{j,t}^P - \zeta^{(1)} + \zeta^{(2)} - \zeta^{(3)}$. Similarly, for the $\mathbf{TD^{opt}}$ model, we have:

$$\lambda_{\infty,t}^P \sum_n z_{j,n,t}(1+m_{n,t}) + A = 0. \quad (31)$$

Not surprisingly, the optimality conditions for $\mathbf{TD^{opt}}$ and the distributed $\mathbf{EV^{opt}}$ model without feeder information, are identical. The reason is that the latter is a decomposition of the former, yielding the same optimal solution.

Lastly, for the $\mathbf{EV_F^{opt}}$ model, we have:

$$\lambda_{\infty,t}^P \sum_n z_{j,n,t}(1+m_{n,t}) + \lambda_{\infty,t}^P \sum_n z_{j,n,t}\gamma_n q_{j,t}^P - \lambda_{\infty,t}^R \sum_n z_{j,n,t}\gamma_n q_{j,t}^R + A = 0. \quad (32)$$

We observe that (30)–(32) contain different terms, implying different optimal solutions. We clarify that even in the same terms, i.e., the first and last term, their optimal values will most likely differ in the above models. Nevertheless, the "mismatch terms" imply potential causes of the differences. By inspection, we observe that (31) is missing the second term of (30) that contains the coupling of energy and reserve. The coupling appears in (32), however, it includes only the individual EV reserve provision $q_{j,t}^R$ and not the sum $(\sum_{j\in J_{n,t}} q_{j,t}^R)$. Lastly, we note that the "mismatch terms" contain γ_n, and that the lower this value the weaker the impact of these terms.

V. Numerical Results

For illustration purposes, we employ a simple network, with $N = 2$ distribution nodes. We list the input data (Subsection V-A), and present the results (Subsection V-B).

A. Input Data

The inelastic demand daily load profile is shown in Figure 2. Reserve requirements are set to 7% of total inelastic demand. Conventional generator data (total capacity 700 MW) are listed in Table I. EVs are classified in 7 groups based on their characteristics and preferences. For all groups, traveling plans are assumed to be known *a priori*, which is a reasonable assumption for a day-ahead scheduling problem. The battery capacity for all groups is 24 kWh. The charger capacity is 9 kW for EV groups 4–6 and 12 kW for groups 1–3, and 7. The degradation coefficient is $\epsilon = 4 \times 10^{-6}$ \$/(kWh)^2.

We consider two EV penetration Cases. In Case 1 the aggregate EV minimum consumption is 21 MWh (10.8 at Node 1, 10.2 at Node 2); it is doubled in Case 2. Although EV consumption is low compared to inelastic demand (0.36% in Case 1, and 0.72% in Case 2), EV share in reserve provision is substantial. We list in Table II the EV groups, the number of EVs for each Case, the hours they are connected at each node (subset $T_{j,n}$), and the demand $d_{j,n}$ (in kWh) by the time of departure, which accounts for the estimated consumption, i.e., $d_{j,n}$ refers to the sum of $d_{j,t}$ for the hours of travel following the departure from node n. Assuming a low enough SoC upon arrival, $d_{j,n}$ is the amount of energy EV j should be charged while connected at node n. Initial SoC is appropriately estimated considering the daily pattern.

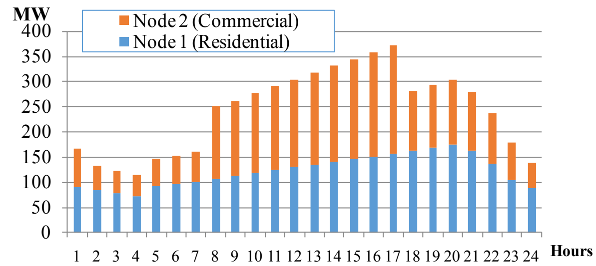

Fig. 2. Inelastic demand load profile

TABLE I
Conventional Generator Data

i	$\overline{Q}_i^P$	$\overline{Q}_i^R$	α_i^P	β_i^P	α_i^R	β_i^R
1	35	5	32	0.038	30	0.084
2	35	5	34.66	0.095	32.94	0.066
3	35	5	41.31	0.03	35.25	0.077
4	35	10	43.41	0.05	37.945	0.076
5	35	10	46.91	0.084	40.605	0.076
6	35	10	52.79	0.065	43.265	0.083
7	35	15	57.34	0.115	46.17	0.065
8	35	15	65.39	0.069	48.445	0.071
9	35	15	70.22	0.071	50.93	0.08
10	35	20	75.19	0.046	53.73	0.078
11	35	20	78.41	0.051	56.46	0.081
12	35	20	81.98	0.072	59.295	0.073
13	35	25	87.02	0.03	61.85	0.069
14	35	25	89.12	0.046	64.265	0.079
15	35	25	92.34	0.027	67.03	0.066
16	35	30	94.23	0.068	69.34	0.074
17	35	30	98.9	0.031	71.93	0.068
18	35	35	101.07	0.06	74.31	0.068
19	35	35	105.27	0.068	76.69	0.082
20	35	35	110.03	0.02	79.56	0.06

TABLE II
EV Data

EV Group	# EVs Case 1	# EVs Case 2	$T_{j,1}$	$d_{j,1}$	$T_{j,2}$	$d_{j,2}$
1	310	620	7pm-7am	12	9am-5pm	12
2	160	320	9am-5pm	12	7pm-7am	12
3	80	160	8pm-7am	6	9am-6pm	6
4	80	160	8pm-7am	12	9am-6pm	9
5	160	320	9pm-7am	12	9am-7pm	9
6	400	800	9pm-7am	0	9am-7pm	6
7	300	600	8pm-1am	6	N/A	N/A

B. Results

The computational experiments were run using AIMMS 4.0, and the distributed model run times were less than 3 minutes, with stepsize parameters set at $\underline{u} = 0.4$ and $\overline{u} = 1.2$. $\mathbf{TD^{opt}}$, $\mathbf{EV^{opt}}$, and $\mathbf{EV_F^{opt}}$ converged in 30, 800, and 1200 iterations, respectively.

In Table III, we summarize the aggregate EV cost (energy cost minus reserve revenues plus degradation cost) for the two Cases. Since the $\mathbf{TD^{opt}}$ and $\mathbf{EV^{opt}}$ models produce the same results, we mention only the latter.

TABLE III

AGGREGATE EV COST

Case 1: Low Penetration	$\mathbf{TD_F^{opt}}$	$\mathbf{EV^{opt}}$	$\mathbf{EV_F^{opt}}$
Aggregate EV cost	348.82	348.67	348.63
Energy cost	1456.27	1456.39	1456.56
Reserve Revenue	1107.88	1108.13	1108.35
Degradation	0.43	0.42	0.41
Case 2: High Penetration	$\mathbf{TD_F^{opt}}$	$\mathbf{EV^{opt}}$	$\mathbf{EV_F^{opt}}$
Aggregate EV cost	718.08	714.75	714.56
Energy cost	2933.62	2935.78	2936.09
Reserve Revenue	2216.35	2221.72	2222.22
Degradation	0.80	0.69	0.69

Energy LMPs are always higher than reserve LMPs, due to generators' higher marginal cost for energy (Table I). Hence, EVs charge at hours with lower LMPs (at most 9 hours), and at the minimum required amount. EVs are generally connected long enough and flexible in providing reserves; the optimal solution is to provide the maximum amount possible, i.e., $q_{j,t}^R$ is equal to $q_{j,t}^P$. Therefore, contrary to their low energy consumption share, EV reserve provision reaches up to 96% of the reserve requirements in some hours (Figure 3). We also observe that EVs reduce their total cost when they self-schedule (in the $\mathbf{EV^{opt}}$ and $\mathbf{EV_F^{opt}}$ models), by increasing their reserve revenue at the expense of energy cost; in fact, they do slightly better when they have local feeder information, by reallocating their charging across hours. As expected, the global model $\mathbf{TD_F^{opt}}$ achieves the lowest social cost.

In the following figures, we examine the hourly differences in total EV consumption and reserve provision, as well as prices across the $\mathbf{TD_F^{opt}}$, $\mathbf{EV^{opt}}$, and $\mathbf{EV_F^{opt}}$ models, for Case 2. For simplicity, we show the hours with nonzero EV consumption. Figure 3 shows the total reserve provision of EVs and generators at the substation level, whereas Figure 4 shows the total EV consumption, energy and reserve LMPs. Since the price differences between the distributed models are small, we only show prices for $\mathbf{TD_F^{opt}}$ and $\mathbf{EV_F^{opt}}$.

When EVs provide more reserves in the $\mathbf{TD_F^{opt}}$ model, reserve LMPs expectedly become lower in these hours, since generators need to provide less to meet the system requirements (e.g., hours 2, 3, 4, and 18). The opposite is generally true for energy consumption; when all EVs consume more in the $\mathbf{TD_F^{opt}}$ model, energy LMPs are also higher. However, energy LMPs in hours 2 and 4 seem to be unaffected from higher EV consumption in the $\mathbf{TD_F^{opt}}$ model (Figure 4). This is because hourly energy balance and required generation depends on the losses. For instance, Figure 5 shows that in hour 2, EV consumption in the $\mathbf{TD_F^{opt}}$ model is higher in Node 1, but lower in Node 2; this has opposing effects on the total losses in that hour.

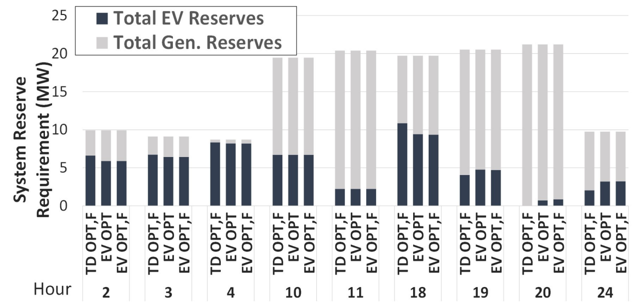

Fig. 3. Reserve provision at the substation level.

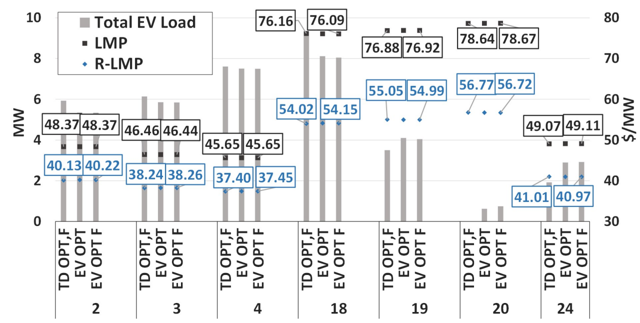

Fig. 4. Hourly EV consumption, energy and reserve LMPs.

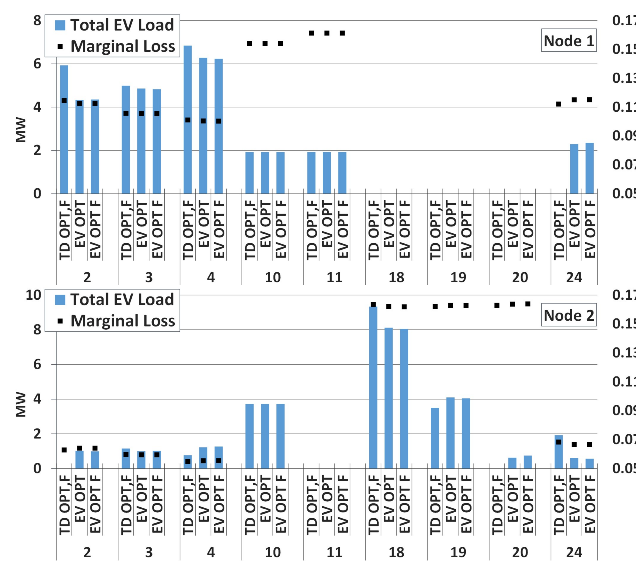

Fig. 5. EV consumption and marginal losses (Nodes 1 and 2).

The general trend of increasing EV charging costs (net of reserve sales revenue) as EVs are scheduled respectively by the $\mathbf{EV^{opt}}$, $\mathbf{EV_F^{opt}}$ and $\mathbf{TD_F^{opt}}$ models is explored further by considering EV group specific results. Table IV shows that EV groups 2, 6 and 7 which are connected during hours when marginal losses are low, cannot compete effectively with the rest of the groups (1, 3, 4, 5) that are connected during high marginal loss hours. Indeed, the value of feeder information to compete and reduce their costs under $\mathbf{EV_F^{opt}}$ scheduling relative to $\mathbf{EV^{opt}}$ scheduling is smaller for groups 2, 6, and 7. In addition, Group 7 stands out to the extent that the global information schedule $\mathbf{TD_F^{opt}}$ increases its charging cost disproportionately relative to other groups, while EV Group 2 is relatively unaffected.

TABLE IV
EV GROUP RESULTS

Group	$\mathbf{TD_F^{opt}}$ **(1)**	$\mathbf{EV^{opt}}$ **(2)**	$\mathbf{EV_F^{opt}}$ **(3)**	**(4)=(2)-(3)**	**(5)=(3)-(1)**
1	260.65	259.23	259.16	0.029	-0.576
2	129.22	129.23	129.22	0.005	0.002
3	33.36	33.19	33.17	0.049	-0.576
4	54.38	54.15	54.13	0.044	-0.464
5	84.28	83.79	83.75	0.041	-0.632
6	123.06	122.48	122.44	0.031	-0.507
7	33.14	32.69	32.69	-0.013	-1.353

VI. CONCLUSIONS

We propose a tractable day-ahead energy and reserve scheduling algorithm with centralized generators connected to the Transmission network as well as DERs and price inelastic consumption connected to Distribution network feeders. Tractability requires decomposition to multiple individual DER scheduling problems that solve for given nodal marginal cost based prices and iterate with a T&D Network model updating prices till convergence. Focusing on the existence and severity of strategic behavior, we consider the significance of access by the self-scheduling DERs to local feeder information enabling them to anticipate the impact of their scheduling decisions on distribution network prices that determine their net costs. Our analysis shows that strategic behavior is enabled by DER local feeder information access. Although DER schedules are only slightly modified, the distribution of costs and benefits among market participant groups and among competing DERs is affected.

The numerical results that we provide demonstrate the trends anticipated by the analytically documented differences between the distributed scheduling algorithms with and without DER access to local feeder information. The relatively small impact of DER information access on social welfare and the distribution of benefits amongst participants supports the idea of proceeding with future T&D market designs that discourage local feeder information access. This implies that there is a potential advantage to discourage the role of distribution network operators as DER aggregators and investigate information platforms that enable individual DERs to participate in distributed decision making as price takers at their respective nodes.

Notably, requisite distributed algorithms with accurate AC OPF capability have been proposed and tested on real size systems. Our reliance on and use of a simplified network flow model in this paper, was simply a choice made to facilitate the analysis of strategic behavior. We have also shown on a separate and ongoing work the existence and uniqueness of the Nash equilibrium in the non-cooperative game EVs engage in when they have access to the local feeder information.

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