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Management of Electric Vehicle Charging to Mitigate Renewable Generation Intermittency and Distribution Network Congestion

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Abstract—We consider the management of electric vehicle (EV) loads within a market-based Electric Power System Control Area. EV load management achieves cost savings in both (i) EV battery charging and (ii) the provision of additional regulation service required by wind farm expansion. More specifically, we develop a decision support method for an EV Load Aggregator or Energy Service Company (ESCo) that controls the battery charging for a fleet of EVs. A hierarchical decision making methodology is proposed for hedging in the day-ahead market and for playing the real-time market in a manner that yields regulation service revenues and allows for negotiated discounts on the use of distribution network payments. Amongst several potential solutions that are available, we employ a rolling horizon look-ahead stochastic dynamic programming algorithm and report some typical computational experience.

I. Introduction

A. Wind Generation and EV Charging Synergies

A sustainable energy future will have to rely beyond conservation and efficiency gains to (i) the conversion of transportation vehicles, responsible today for 30% of CO_2 emissions in the United States, to EVs and (ii) the commensurate adoption of now economically competitive [17] clean renewable energy generation. We address a decision support problem that is central to the realization of an important synergy between the management of EV battery charging and the alleviation of congestion in both the distribution network infrastructure and fast reserve capacity (regulation service). Indeed, wind generation's intermittency requires additional reserve capacity, of the order of 10-20% of wind capacity [10]-[11], [14]. Given that regulation service, which is provided today by fast reserve capacity of the order of 1-2% of load, costs $40-$50 per MW per hour [23], a four to five fold increase will certainly raise its cost and hinder the adoption of renewable generation. At the same time, the advent of EVs will increase load substantially and, in the absence of smart charging, require costly distribution network investments that may easily become a show stopper for widespread EV adoption. We claim that EV battery charging can be managed so as to *both* increase the supply of regulation service thus controlling its cost *and* mitigate distribution network congestion.

In order to streamline our presentation, we assume that (i) an ESCo is selected by EV owners to manage EV charging; (ii) EVs are equipped with a smart interface that measures in real-time, the energy needed to fully charge the EV batteries, identifies the location of the outlet the EV is plugged-in, and accepts EV owner input about the desired departure time; and (iii) the ESCo recovers information at will from each EV smart interface, controls battery charging in real-time, and communicates with the distribution network operator who provides information on low voltage feeder specific unused capacity available for EV battery charging.

In this paper we propose a decision support methodology for the ESCo to manage EV battery charging while engaging in energy and reserve capacity transactions in the wholesale power market. Given the important role of the wholesale market in the ESCo costs and revenues, we describe next the framework that we assume to be in place. In contrast we do not go through the details of the retail market since we assume that related ESCo benefits derive from a long term contract subject to the ESCo observing feeder congestion constraints.

B. Day-Ahead and Real-Time Wholesale Markets

We assume an operative day-ahead and real-time power market framework similar to that used in the major USA power pools (PJM, NYISO, NEISO, MISO, ERCOT, California ISO) but somewhat simplified and stylized without loss of generality since the essential characteristics are retained. The actual PJM and NYISO market practice is presented in [18]-[22] while work by the authors on real-time pricing and power market design can be found in [2], [4]-[9], [16]. The products traded and cleared in the wholesale market include nodal energy injections and withdrawals needed to achieve real-time energy balance, and Independent System Operator (ISO) determined levels of area-specific capacity reserve requirements secured by the ISO from several participants, who also offer/demand energy using the same hardware. Capacity reserves consist of (i) frequency control, usually a fast reacting up/down band of capacity provided by real-time frequency deviation automatic generation control totaling today 0.1-0.3% of load with full deployment capability required in 30 seconds, (ii) regulation service, a similar up/down band of capacity that the ISO issues commands to every 5-8 seconds totaling today 1-2% of load, with full deployment capability required in 5 minutes (iii) spinning or operating reserves that the ISO may call to provide energy within 15 minutes, totaling an

additional 3-6% of peak load or the size of the largest contingency, and (iv) slower reserves (0.5 to 2+ hour response).

The *day-ahead market* closes at noon of the previous day and uses participant bids to determine an hourly schedule of energy and reserve products together with the corresponding clearing prices at each node of the transmission network. This is done by selecting hourly energy and reserve quantities that maximize consumer plus producer surplus subject to energy balance, transmission constraints, reserve requirement and other technical constraints such as ramp constraints, minimal generation, and down and up times. The usual methodology employed by the ISO is a mixed integer LP mathematical program.

The *real-time market* allows adjustments relative to the day-ahead market clearing energy and reserve quantities and prices at the beginning of every 5 minute interval. Reserve requirement constraints are reinforced by re-dispatching net energy injections to return reserve capacity to its nominal operating levels. As a result, the diversions of regulation service in the seconds scale appear like white noise with minimal (close to zero) impact on the energy provided over time periods greater than 30 minutes. The usual methodology employed by the ISO is the solution of a rolling 1-2 hour horizon optimization model that determines the next 5 minute quantity schedule and clearing prices while providing forecasts for the next few 10-15 minute periods.

In order for a regulation service offer (in KW) Q_t^R to be accepted, (i) the nominal consumption rate must be Q_t^R so that it can be modulated at the ISO's discretion in the interval $[0, 2Q_t^R]$, and (ii) the regulation service clearing price, P_t^R, must exceed the opportunity cost of consuming at Q_t^R rather than at 0 or $2Q_t^R$ plus the price offered for engaging in the fast regulation service modulation, u_t^{RC}. In fact, denoting the energy clearing price by P_t^E and the energy price bid for consuming at the rate Q_t^R by u_t^{RE}, we observe that the unit opportunity cost is $|P_t^E - u_t^{RE}|$. When $P_t^E < u_t^{RE}$ the opportunity cost of operating at Q_t^R rather than at $2Q_t^R$ is $(u_t^{RE} - P_t^E)Q_t^R$, while when $P_t^E > u_t^{RE}$ the opportunity cost of operating at Q_t^R rather than at 0 is $(P_t^E - u_t^{RE})Q_t^R$. In conclusion, the co-optimization of energy and reserve capacity results in the criterion that a regulation service offer Q_t^R is accepted when $|P_t^E - u_t^{RE}| + u_t^{RC} \le P_t^R$.

C. ESCo Role in EV Battery Charging

The ESCo is assumed to be a participant in the wholesale market where it hedges its energy costs by purchases in the day-ahead market, and then adjusts to its actual needs by buying excess or selling surplus in the real-time market. The ESCo offers regulation service in the real-time market under the usual obligation to respond to ISO for the corresponding consumption. The ESCo is assumed to receive information on the excess load capacity at each feeder line, and to be able to contract with the distribution network owner for discounts on the distribution fee, provided that EV battery charging does not impose loads that exceed the excess capacity of each feeder. The ESCo (i) incurs daily costs in the day-ahead market (ii) adjusted through purchases in the real-time market, (iii) enjoys revenues through real-time regulation service sales, and (iv) receives monthly distribution network fee discounts [5], [8]-[9], [25] provided it observes feeder excess capacity limitations in real-time. Decisions the ESCo must make at different time scales are:

1. *Daily*, day-ahead market, noon of day before: bid energy quantities and prices for each of the 24 hours in the upcoming day. In some regions there are "rebalancing" markets that follow the day-ahead market to reschedule or adjust unit commitment after uncertainty is realized.

2. *Hour-to-5-minute*, real-time market (at the beginning of each real-time market period): (i) request what we call "for sure" charging rate quantity, Q_t^E, accompanied by a high enough price bid, u_t^E, to assure the quantity is accepted, and (ii) offer bidirectional regulation service capacity, Q_t^R, accompanied by a pair of price bids u_t^{RE}, u_t^{RC} for energy and capacity, respectively. In addition, the ESCo must follow market rules to make sure that its consumption rate bid and regulation service offer are realizable. This requires that the following two constraints on the maximal consumption rate (i.e. the requested consumption rate plus *twice* the offered regulation service): *first* there must be enough plugged-in EVs to absorb the maximal charging rate in the event all of the regulation service consumption capacity is required, and *second* the excess load capacity of each feeder should be sufficient to support the maximal consumption rate in that feeder.

3. *Seconds*, operational level: Adjust the total charging rate in each feeder to satisfy regulation service commands without exceeding feeder capacity limits and distribute feeder charging rate to individual battery charger commands. A reasonable and probably near optimal policy for the latter is to do it by pursuing the target of equal charged level across batteries of all feeder connected EVs with the same departure time. This is a good strategy because on the one hand it maximizes the number of EVs that can provide positive regulation service load, while on the other it spreads equitably the risk that a large portion of a particular EV's battery is uncharged at the time of departure.

II. HOUR-TO-5-MINUTE FEEDER SUB-PROBLEM

We start with rigorous definitions leading to a dynamic programming formulation of the feeder sub-problem. A short discussion of how the sub-problem fits in the overall problem is followed by brief commentary on alternative sub-problem solution approaches. We propose a Finite Look-Ahead Dynamic Programming approximation which we apply to explore various numerical solutions in Section III.

We focus on the real-time market decisions over a finite horizon. Without loss of generality we assume that (i) periods can be of variable length to take advantage of the fact that market and feeder conditions are occasionally similar over a number of hours; (ii) the battery charging rate for each vehicle can be switched at will between two discrete positions, 0 and a fixed rate (say 2KW); (iii) the ESCo receives feeder specific capacity forecasts; (iv) the ESCo has access to a joint probability distribution (jpd) of energy and regulation service clearing prices; (v) the ESCo has feeder specific forecasts of when EVs are expected to connect including their departure time; (vi) the ESCo is a price taker in the "for sure" energy market; and (vii) no cars un-plug from a feeder location before their declared departure time. The following lists develop the notation necessary for problem formulation.

Random Variables, Density Functions, and Exogenous Estimates

$t, \Delta t$: Decision period t and its duration.

$\hat{W}_t^{t^*}, \hat{Y}_t^{t^*}$: Wind output and system outage state during period t, as forecasted at $t^* \leq t$.

$\hat{C}_t^{\max,t^*}$: Feeder specific unused capacity available for EV battery charging at time t as forecasted at $t^* \leq t$.

$\hat{\Delta}n_t^{\tau}(t^*), \hat{\Delta}x_t^{\tau}(t^*)$: Number of EVs and their uncharged energy expected to plug-in during period t with declared departure at the beginning of period τ, forecasted at $t^* \leq t$.

$\mathbf{E}_{t^*}$: Expectation operator conditional on information available at the beginning of period $t^* \leq t$.

P_t^E, P_t^R : Realized real-time market clearing prices during period t for energy and regulation service.

$f_{t^*}(P_t^E, P_t^R \mid \hat{W}_t^{t^*}, \hat{Y}_t^{t^*})$: Jpd of energy and regulation service clearing prices given information available at $t^* \leq t$.

State and Decision Variables

n_t^{τ}, x_t^{τ} : Number of EVs and their uncharged energy plugged-in at the beginning of period t, with declared departure the beginning of period τ.

$\hat{\theta}_t^{t^*}$: State augmentation with forecasts $\hat{W}_t^{t^*}$, $\hat{Y}_t^{t^*}$, and $\hat{C}_t^{\max,t^*}$ available at $t^* \leq t$.

$Q_t^E(\tau), Q_t^R(\tau)$: Energy rate requested during period t, and regulation service capacity offered at time t, respectively. Related to charging EVs with battery space x_t^{τ}.

$u_t^{RE}(\tau), u_t^{RC}(\tau)$: Energy and capacity price offered, respectively, for $Q_t^R(\tau)$.

Parameter Values

c : Penalty per KWh of uncharged energy at time of EV departure.

λ_N : Estimated marginal cost of charging x_N^{N+1}.

r : The charging rate of each EV.

The total expected costs includes the sum of the costs for each period t included in the finite look-ahead (1) and terminal costs (2). It is important to note that these values depend on $\hat{\theta}_t^{t^*}$.

$$cx_t^t + \sum_{\tau} \mathbf{E}_{t^*}\{P_t^E Q_t^E(\tau) + [P_t^E - P_t^R]Q_t^R(\tau)\Pi_t^{\tau}(t^*)\}\Delta t \tag{1}$$

$$cx_N^N + \lambda_N x_N^{N+1} \tag{2}$$

A. Dynamics and Allowable Decisions

The dynamics and allowable decisions depend on the decisions $u_t^{RE}(\tau)$, $u_t^{RC}(\tau)$ and the state augmentation $\hat{\theta}_t^{t^*}$. For all $\tau > t$ the energy state dynamics can be written using the unit function $1_{Q_t^R(\tau)\text{accept}}$ that equals 1 if $Q_t^R(\tau)$ is accepted, 0 otherwise.

The probability that a regulation service bid is accepted, which we will denote $\Pr(1_{Q_t^R(\tau)\text{accept}} = 1) \triangleq \Pi_t^{\tau}(t^*)$, is obtained as noted from $f_t(P_t^E, P_t^R \mid \hat{W}_t^{t^*}, \hat{Y}_t^{t^*})$ using the methodology described above. Therefore, the state dynamics can be expressed in (3)-(5).

$$n_{t+1}^{\tau} = n_t^{\tau} + \hat{\Delta}n_t^{\tau}(t^*) \text{ but for } \tau \leq t, \ n_t^{\tau} = \Delta n_t^{\tau}(t) = 0 \tag{3}$$

$$x_{t+1}^{\tau} = x_t^{\tau} + \hat{\Delta}x_t^{\tau}(t) - [Q_t^E(\tau) + 1_{Q_t^R(\tau)\text{accept}} Q_t^R(\tau)]\Delta t \tag{4}$$

$$\hat{\theta}_{t+1}^{t+1} = [\hat{W}_{t+1}^{t+1}, \hat{Y}_{t+1}^{t+1}, \hat{C}_{t+1}^{\max,t+1}] \tag{5}$$

Equations (6)-(8) present the feeder capacity constraints that guarantee the ability to provide the full regulation service if requested by the ISO.

$$\Sigma_{\tau}[Q_t^E(\tau) + 2Q_t^R(\tau)] \leq \hat{C}_t^{\max,t^*} \tag{6}$$

$$Q_t^E(\tau) + 2Q_t^R(\tau) \leq rn_t^{\tau} \tag{7}$$

$$\left[Q_t^E(\tau) + Q_t^R(\tau)\right]\Delta t \leq x_t^{\tau} \tag{8}$$

B. Hour-to-5-Minute Feeder Sub-Problem Formulation

We formulate the hour-to-5-minute time scale feeder sub-problem as a finite horizon stochastic dynamic programming problem (SDP). In the following formulation of the SDP (9),

decisions are made at the beginning of each period employing accurate estimates available at $t* = t$.

$$\min_{Q_t^E(\tau), Q_t^R(\tau), u_t^{RC}(\tau), u_t^{RE}(\tau), \forall t, \tau} \Sigma_t \left\{ cx_t^t + \Sigma_\tau \mathbf{E}_t \{ P_t^E Q_t^E(\tau) \right.$$
$$\left. + 1_{Q^R(\tau) accept} [P_t^E - P_t^R] Q_t^R(\tau) \} \Delta t \right\} + cx_N^N + \lambda_N x_N^{N+1} \quad (9)$$

Decisions are subject to the state dynamics $\forall t \leq N$ in (3)-(5), allowable control constraints (6)-(8), and non-negativity constraints on the uncharged energy and energy rate bids. Note that $Q_t^E(\tau)$ and $Q_t^R(\tau)$ equal 0 for all $\tau \leq t$.

The problem formulated above is a sub-problem in the hour-to-5-minute time scale. Decisions at each feeder associated with the same time period t are coupled across feeders through hedging transactions in the day-ahead market that secure a certain quantity of energy at the corresponding hour's day-ahead market clearing price. The day-ahead price provides an opportunity cost for real-time transactions which depends on the difference between the day ahead and real-time prices. This opportunity cost reveals itself as the dual variable associated with the balance between the day ahead secured energy and the real-time energy consumption decision. This constraint has been left out in the current formulation but can be incorporated in a Lagrangian relaxation approach that combines a master problem solution at the day-ahead market time scale with multiple feeder specific sub-problems at the real-time market time scale. Extensive work in time scale decomposition approaches by the authors and others [1], [3], [12], [15] has shown that the frequency separation of decisions in the day-ahead and real-time markets is sufficient to provide near optimal and rapidly converging formulations.

The periodic infinite horizon issue is addressed through the inclusion of an extension period model reflected in the terminal cost approximation where uncharged batteries of EVs with declared departure after the end of the horizon ($\tau > N$) are penalized by a fixed cost rate (λ_N) estimated to represent the marginal cost of charging them in the future. A better approximation would be to use departure time specific cost rates and to estimate these rates by running an explicit extension period model.

III. Solution Approach Adopted

Obtaining the optimal solution of the proposed finite horizon SDP sub-problem is formidable in itself due to (i) the large state and control space, and (ii) the non-linearity introduced in the dynamics by the probability that regulation service offers will be accepted. Amongst the various tractable but potentially near optimal approximations proposed in the literature we consider conversion to a deterministic problem using robust arguments. We approximate the SDP with an optimal open loop feedback formulation that essentially coincides with a finite period look-ahead approach. This look-ahead approach increases the number of decision variables since they now depend on

the forward trajectories that are created and defined above for each acceptance or rejection of the regulation service offer for each t and τ. We also have to keep track of these forward trajectories and associate all decisions and state variables at each time period t with each possible trajectory from time 0 to time t. We define $S_{k(t)}^\tau = \left[s_{k(t),1}^\tau, ..., s_{k(t),\ell}^\tau, ..., s_{k(t),t}^\tau \right]$ as a $1 \times t$ vector with elements in $\{0,1\}$ corresponding to the rejection or acceptance of a regulation service offer. The counter $k(t)$ takes values in $\{1, 2, 3, ..., 2^t\}$ to span all possible 2^t trajectories that state variables may evolve from period 0 to the beginning of period t forming an acyclic tree of network trajectories. $S_{k(t)}^\tau$ evolves according to a forward recursive relationship that depends on the acceptance or rejection of the regulation service offer for period t intended to charge EVs plugged-in prior to period t and planning to depart at the beginning of period $\tau > t$. The recursion is based on the fact that each trajectory $k(t)$ generates 2 trajectories k' and k'' at $t+1$ through the concatenation of elements $s_{k'(t+1),t+1}, s_{k''(t+1),t+1}$, with assigned probabilities as known at $t* = 0$. Since state and decision variables, except for n_t^τ and $\hat{\theta}_t^0$, are now conditional upon the trajectory $S_{k(t)}^\tau$, we must write $x_t^\tau(S_{k(t)}^\tau)$, $Q_t^R(\tau, S_{k(t)}^\tau)$, $Q_t^E(\tau, S_{k(t)}^\tau)$, $u_t^{RE}(\tau, S_{k(t)})$, and $u_t^{RC}(\tau, S_{k(t)})$. *Note that now acceptance probabilities are trajectory dependent, since the price offers are trajectory dependent.* Letting $\Pi_t(0, S_{k(t)}^j)$ be the probability that offer $Q_t^R(\tau, S_{k(t)}^\tau)$ is accepted, we have the trajectory probabilities recursion shown in (10)-(11).

$$S_{k'(t+1)}^\tau = [S_{k(t)}^\tau, 0], \text{ with}$$
$$\text{PrTr}(S_{k'(t+1)}^\tau) \triangleq \text{PrTr}(S_{k(t)}^\tau)(1 - \Pi_t(0, S_{k(t)}^\tau)) \quad (10)$$

$$S_{k''(t+1)}^\tau = [S_{k(t)}^\tau, 1], \text{ with}$$
$$\text{PrTr}(S_{k''(t+1)}^\tau) \triangleq \text{PrTr}(S_{k(t)}^\tau) \Pi_t(0, S_{k(t)}^\tau) \quad (11)$$

and initial condition $\text{PrTr}(S_{k(0)}^\tau) = 1$. Based on the knowledge of estimates at $t* = 0$, $\Pi_t(0, S_{k(t)}^j)$ is calculated from the known jpd $f_0(P_t^E, P_t^R | \hat{W}_t^0, \hat{Y}_t^0)$, and period decisions are made for every $k(t)$. *The finite look-ahead dynamic problem (LADP) expressed in (12).* Subject to state dynamics equations $\forall t \leq N$ presented in (3) and (13)-(14), the trajectory probabilities recursion presented in (10)-(11) with the initial condition $\text{PrTr}(S_{k(0)}^\tau) = 1$, allowable control constraints in (15)-(17), and non-negativity constraints on the uncharged energy and energy rate bids. Note that $Q_t^E(\tau, S_{k(t)})$ and $Q_t^R(\tau, S_{k(t)})$ equal 0 for all $\tau \leq t$.

$$\min_{Q^E, Q^R, u^{RC}, u^{RE}} \Sigma_t \left\{ cx_t^t + \Sigma_{\tau,k} \mathrm{PrTr}(S_{k(t)}^\tau) \mathbf{E}_0 \{ P_t^E Q_t^E(\tau, S_{k(t)}^\tau) \right.$$

$$+ [P_t^E - P_t^R] Q_t^R(\tau, S_{k(t)}^\tau) \Pi_t(0, S_{k(t)}^\tau) \} \Delta t \right\} \qquad (12)$$

$$+ \Sigma_k \mathrm{Pr\,Tr}(S_{k(N)}^N) cx_N^N(S_{k(N)}^N)$$

$$+ \Sigma_k \mathrm{Pr\,Tr}(S_{k(N)}^{N+1}) \lambda_N x_N^{N+1}(S_{k(N)}^{N+1})$$

$$x_{t+1}^\tau(S_{k'(t+1)}^\tau) = x_t^\tau(\tau, S_{k(t)}^\tau) + \hat{\Delta} x_t^\tau(0) - Q_t^E(\tau, S_{k(t)}^\tau) \Delta t \qquad (13)$$

$$x_{t+1}^\tau(S_{k'(t+1)}^\tau) = x_t^\tau(S_{k(t)}^\tau) + \hat{\Delta} x_t^\tau(0) - [Q_t^E(S_{k(t)}^\tau) + Q_t^R(S_{k(t)}^\tau)] \Delta t \qquad (14)$$

$$\Sigma_\tau [Q_t^E(\tau, S_{k(t)}) + 2 Q_t^R(\tau, S_{k(t)})] \leq \hat{C}_t^{\max,0} \qquad (15)$$

$$Q_t^E(\tau, S_{k(t)}) + 2 Q_t^R(\tau, S_{k(t)}) \leq r n_t^\tau \qquad (16)$$

$$\left[Q_t^E(\tau, S_{k(t)}) + Q_t^R(\tau, S_{k(t)}) \right] \Delta t \leq x_t^\tau(S_{k(t)}^\tau) \qquad (17)$$

Based on robust arguments (i.e., worst case analysis) we use conservative but anticipatory estimates of feeder excess capacity and new EV arrivals. Whereas the joint probability of clearing prices the next 90 minutes is known with small variance, and the wind and system state estimates are also known well on an hour ahead basis, there is a higher forecast error for periods further in the future. This problem is somewhat mitigated by using an optimal open loop feedback approach and using only the decisions for $t = 0$, and then resolving at $t = 1$, etc.

We select $u_t^{RE}(\tau, S_{k(t)}^\tau)$ as the forecasted energy price and let $u_t^{RC}(\tau, S_{k(t)}^\tau)$ be zero, which allows us to stay within the convenience of linear programming. Therefore, the probability that the regulation service offer is accepted is maximized. In addition the probability a regulation service bid is accepted is no longer a function of τ. This simplification is consistent with the EV load aggregator being a price taker and results in a single trajectory set that applies to all EV groups. The look-ahead formulation results in a classic tree structure.

IV. COMPUTATIONAL RESULTS

We employed a four period look-ahead model, $t \in \{0, 1, 2, 3\}$ with extension period $\tau = 4$. Each period was assumed to consist of 6 relatively homogeneous hours with $t = 0$ corresponding to 6:00 P.M. The model input was calibrated to represent a low voltage residential feeder servicing approximately fifty households with an equal number of EVs in Texas where wind farm generation is already substantial and is likely to continue to develop at a rate amongst the fastest in the United States. Typical fall and summer residential consumption profiles and hourly wholesale market energy and regulation service prices were drawn from the ERCOT website. This information was complemented by reasonable assumptions on distribution capacity and residential EV battery charge demand patterns as shown in Fig. 1 and Tables I-II.
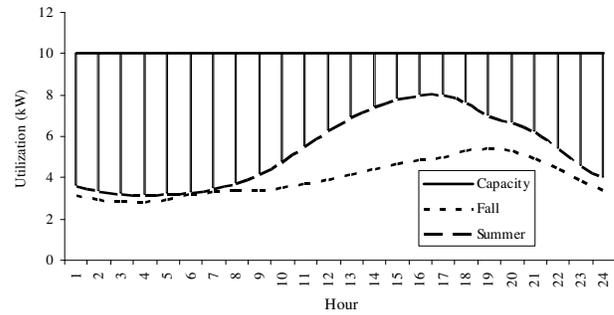
Fig. 1. Non-EV load profiles. Hour 1 corresponds to 12:01 A.M. to 1:00 A.M. The vertical lines in the graph show $\hat{C}_t^{\max,0}$.

TABLE I
EXPECTED EV BATTERY CHARGE DEMAND

Values	$\tau=1$	$\tau=2$	$\tau=3$	$\tau=4$	$\tau=4+$
x_0^τ	4	212	48	24	12
n_0^τ	1	20	5	2	1
$\Delta x_0^\tau(0)$	n/a	220	0	20	0
$\Delta x_1^\tau(0)$	n/a	n/a	4	8	12
$\Delta x_2^\tau(0)$	n/a	n/a	n/a	8	20
$\Delta x_3^\tau(0)$	n/a	n/a	n/a	n/a	300
$\Delta n_0^\tau(0)$	n/a	20	0	2	0
$\Delta n_1^\tau(0)$	n/a	n/a	1	1	1
$\Delta n_2^\tau(0)$	n/a	n/a	n/a	1	3
$\Delta n_3^\tau(0)$	n/a	n/a	n/a	n/a	29

Selected for a residential community in a typical work day.

TABLE II
EXPECTED WHOLESALE MARKET CLEARING PRICES

t	Fall			Summer		
	$\mathbf{E}_0[P_t^E]$	$\mathbf{E}_0[P_t^R]$	$\Pi_t(0)$	$\mathbf{E}_0[P_t^E]$	$\mathbf{E}_0[P_t^R]$	$\Pi_t(0)$
0	0.048	0.020	0.90	0.102	0.033	0.88
1	0.022	0.015	0.80	0.061	0.014	0.80
2	0.040	0.017	0.85	0.075	0.019	0.83
3	0.068	0.019	0.89	0.157	0.045	0.90

$ per KWh. $\Pi_t(0)$ values correlated to expected clearing prices.

Parameter Values Used

c : $0.75 per KWh corresponds to $3 per gallon of gasoline.
λ : Set equal to the average cost of charging energy during the control horizon. Since this average cost depends on the value of λ, several runs had to be made to assure convergence.
r : 2 KW.

Distribution losses were assumed to be 5%, 7.5% and 10% during low peak, intermediate and peak load conditions, respectively. Transmission and distribution usage fees were assumed to be of the order of $0.06 per KWh, and we considered that the ESCo will be able to negotiate a

reduction of $0.02 per KWh consumed in exchange for observing congestion constraints.

The fall simulation resulted in all vehicles being charged prior to their terminal times in all sixteen possible trajectories. The expected average cost (for energy charged and extension period costs) was $0.0249 per KWh. Energy charged in the form of regulation service was expected to account for 17.2% of total EV daily load. Similarly, the summer simulation resulted in all vehicles being charged prior to their declared departure times in all of the sixteen possible trajectories. As one would guess, the expected average cost was significantly higher at $0.0760 per KWh. Energy charged in the form of regulation service was expected to account for 13.9% of total EV daily load. This value is lower due to the higher non-EV load during a typical summer day.

Assuming the $0.02 per KWh reduction in distribution costs, and adding the benefit from low energy cost purchases and the sale of regulation service, in the fall scenario the ESCo managed EV battery charging will cost 26.2% less to the end consumer than the cost of charging the EV on demand (i.e., start charging immediately when the EV plugs-in and until the battery is full), while in the summer scenario the savings is 15.6%. The lower percentage is a result of significantly higher energy prices during a typical summer day.

We wish to emphasize that to obtain reliable results that simulate a high EV penetration future, a higher resolution model is needed (e.g., 12 time periods), multiple typical residential and commercial feeder data must be compiled and the coupled feeder problem must be solved. The purpose of the current paper is to provide a *proof of concept* that such emulation is possible and more importantly elaborate the order of magnitude of potential benefits that are achievable through EV battery charging coordination.

V. CONCLUSION

We developed and implemented a decision tool for the coordination of EV battery charging. Results support the notion that management of renewable generation intermittency, distribution network constraints, and EV charging requirements can result in cost savings, mitigate network and reserve capacity congestion, and remove barriers to the widespread adoption of EVs and renewable generation. Future research will focus on (i) better models of the cascading day ahead, rebalancing, and real-time markets that are able to deal with adaptation to uncertainty revelation such as intermittent generation forecast error and the resulting impact on reserve requirements; (ii) algorithmic improvements such as the integration of the hour-to-5-minute feeder sub-problem with the longer time scale day ahead hedging decision and the shorter time scale real-time operational decisions, and the exploration of feeder sub-problem solutions including robust optimization and feature/state aggregation based approximations; and (iii) a more careful representation of distribution network costs as

related to real-time state identification including line and transformer temperature and line losses.

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