Packetized Plug-in Electric Vehicle Charge Management

Pooya Rezaei, *Student Member, IEEE*, Jeff Frolik, *Senior Member*, *IEEE* and Paul Hines*, Member, IEEE*

***Abstract*—Plug-in electric vehicle (PEV) charging could cause significant strain on residential distribution systems, unless technologies and incentives are created to mitigate charging during times of peak residential consumption. This paper describes and evaluates a decentralized and 'packetized' approach to PEV charge management, in which PEV charging is requested and approved for time-limited periods. This method, which is adapted from approaches for bandwidth sharing in communication networks, simultaneously ensures that constraints in the distribution network are satisfied, that communication bandwidth requirements are relatively small, and that each vehicle has fair access to the available power capacity. This paper compares the performance of the packetized approach to an optimization method and a first-come, first-served (FCFS) charging scheme in a test case with a constrained 500 kVA distribution feeder and time-of-use residential electricity pricing. The results show substantial advantages for the packetized approach. The algorithm provides all vehicles with equal access to constrained resources and attains near optimal travel cost performance, with low complexity and communication requirements. The proposed method does not require that vehicles report or record driving patterns, and thus provides benefits over optimization approaches by preserving privacy and reducing computation and bandwidth requirements.**

***Index Terms*—Communication systems, plug-in electric vehicles, smart charging**

I. Introduction

PLUG-IN electric vehicles (PEVs) have the potential to facilitate a transportation future that is less dependent on liquid fossil fuels. However, as PEV market penetration increases, vehicle charging could strain aging power delivery infrastructure. A number of recent papers have shown that increases in PEV charging could have detrimental impacts on medium and low voltage distribution infrastructure (e.g., [1],[2]), particularly where PEV adoption is highly clustered [3]. With mass-produced PEVs coming to market and a range of charging standards (AC Levels 1-3) established [4], it is increasingly important to understand and mitigate negative impacts that PEV charging might have on distribution system components, such as underground cables and transformers.

Implementing effective charge management (CM, also known as smart charging) methods is one step to facilitate the smooth integration of PEVs. Several previous studies (e.g., [1],[2]) show that with effective CM schemes it is possible to support large numbers of electric vehicles even with constrained electric power infrastructure. In many cases it is also possible for PEVs to not only avoid negative impacts on the power grid, but also to provide grid services, through Vehicle-to-Grid (V2G) technology (e.g., [5],[6]).

The CM and V2G control schemes that have been proposed in the literature, or in industry, generally fall into one or both of the following categories:

1. Centralized optimization or control methods in which each vehicle submits information to a central authority, which in turn solves an optimization problem that produces a charging schedule for each vehicle [7]-[12].
2. Decentralized methods, in which either utilities set a pricing scheme (e.g., a two-period time-of-use price) and vehicles self-schedule based on those prices [13]-[15], or market-based scheme that generate prices from bid or historical information, to which vehicle charge management devices respond [5],[16]-[20].

These two approaches have a variety of advantages and disadvantages.

Centralized schemes have the advantage that they produce optimal outcomes by minimizing costs and avoiding constraint violations in the distribution system. However, optimization/control methods require that vehicle owners provide information (e.g., willingness to pay or anticipated departure times) to a central authority and give up at least some autonomy over the charging of their PEV. While the load-serving entity would likely compensate the vehicle owner for this loss of control with a reduced rate for electric energy, reduced autonomy could be an impediment to the adoption of CM schemes. In addition, vehicle owners are unlikely to know in advance their exact travel schedule, which complicates the problem.

Dynamic pricing schemes, such as reduced rates for nighttime charging, do not have these disadvantages; drivers are free to choose how to respond to change in prices. However, because not all vehicle owners will be price responsive, price-based schemes do not guarantee that vehicle charging will not produce overloads. In fact, under some conditions, time-differentiated pricing could produce new load peaks that increase, rather than decrease, aging in the distribution infrastructure [2]. The method in [21] seeks to combine the benefits of centralized and dynamic pricing

This work was sponsored in part by the US Dept. of Transportation, through the U. of Vermont Transportation Research Center (Grant TRC039), and in part by Carnegie Mellon University's RenewElec project.

The authors are with the School of Engineering at the University of Vermont, Burlington, VT 05405, USA (e-mail: {pooya.rezaei, jeff.frolik, paul.hines}@uvm.edu).

schemes, but has the disadvantage that customers need to declare their willingness to pay for electricity in order to set the parameters for the bidding system. One major impediment for purely price-based schemes is the concern expressed by many utilities that true real-time pricing schemes would not be acceptable to electricity customers [22].

The stochastic nature of charging behavior is particularly important to highlight. PEV arrival and departure times vary substantially among different owners, days, and times-of-day. While aggregate load for a region can be predicted with some accuracy, distribution feeder loads are less predictable, due to the smaller number of customers over which to average. Distribution system load variability and uncertainty will grow even further with an increase in distributed renewable generation. Vehicle CM schemes that do not adapt well to this uncertainty are unlikely to be successful.

The combination of random supply (available capacity on a feeder, for example) and random demand for PEV charging is analogous to the problem of sharing a constrained channel in multiple access communication systems. This paper proposes an approach where PEV charging is completed over multiple short intervals using 'charge-packets,' which are analogous to discrete 'data packets' that revolutionized communications. Our approach leverages a probabilistic automaton, the design of which originated in the decentralized control of node activity in wireless sensor networks [24]. While the packetized approach could be applied in a variety of power system contexts, this paper focuses on the problem of ensuring that PEV charging does not result in overloads in residential distribution components (e.g., transformers or underground cables). Simulation results (Sec. V) show that the inherent randomness in vehicle charging enables constrained resources to be fairly and anonymously shared.

Our approach builds on previous work by the authors and others applying communication algorithms to the problem of PEV charging. We extend our prior work [29]-[31] by simulating realistic travel demand behavior, and by comparing the packetized approach with other approaches to CM. Another communication-inspired algorithm is proposed in [25], which uses a more complicated communication algorithm, in order to treat PEV charging as a continuously controllable variable. Unlike many proposed smart charging methods (e.g., [1],[21]), the charge-packet method does not require drivers to estimate their future departure times.

II. The Communication Channel Analogy

A. Characteristics of Modern Communications

Modern communication systems are characterized not only by information that is digital in format but also by the way that data are sent in multiple discrete packets, each of finite duration. Packet communications can occur over dedicated or shared channels, the latter type we view to have analogous issues to PEVs sharing the power distribution system. In the communications field, techniques that manage access to shared channels (or bandwidth) are collectively known as media access control (MAC) protocols and have as an objective the efficient use of the bandwidth resource (measured by channel throughput) for the load placed on the system [26]. This objective is analogous to matching the demand for power to the available capacity of a feeder, to ensure that high loads do not damage the infrastructure, or trigger instabilities (e.g., voltage collapse). A second objective for MAC protocols is ensuring that latency does not exceed the user's requirements; we view the latency objective to be analogous to PEVs receiving the requisite charge in the requisite time, which is a primary concern to PEV owners. The packetization of data allows both of these conflicting objectives to be addressed simultaneously in communication systems.

B. Packetization of PEV Charge

Why is PEV home charging a candidate for packetized delivery? Firstly, a 5-8kW AC Level 2 PEV charger is likely to be the highest power load in a home; if many chargers in a neighborhood were to run simultaneously, substantial infrastructure degradation could result, particularly in older distribution systems. In addition, most PEV owners with Level 2 chargers will not need to charge their vehicles immediately upon vehicle arrival at home. Given fast charge rates, there is likely to be more than sufficient time overnight to bring a PEV's battery to the desired state of charge (SOC) for the next day's driving. In short, it is typically not necessary that PEV charging be continuous from start to finish.

Packetized charging breaks the required charge time into many small intervals of charging (i.e., 'charge-packets'). For example, 4 hours of Level 2 charging could be accomplished with 48, 5-minute charge-packets. A PEV (or its charging station) would request the authorization to charge for the packet's duration. A charge-management coordinator device at the distribution substation would assess local conditions and determine whether additional load on the system can be accommodated. If allowed, the PEV will charge for the duration of the packet and then submit new requests for subsequent packets until the battery is fully charged. If charging cannot be accommodated, the PEV resubmits a request at a later time.

The accommodation or denial of charging is analogous to the successful transmission of a data packet or a packet collision, respectively, in random access communication systems in which users compete for available bandwidth. Benchmark MAC methods developed for random access channels include Aloha, Slotted-Aloha and Carrier Sense Multiple Access (CSMA) [26], each of which requires very little (if any) overhead communications between the source and loads in the system. The MAC techniques provide a predictable throughput (i.e., utilization of bandwidth) for a given stochastic load by the network as a whole. However, individual user load is not managed by MAC protocols and thus a different type of control is needed if we wish to leverage packetization for the PEV charge management problem.

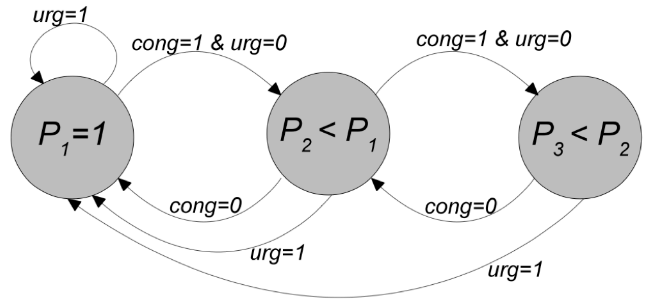

Fig. 1. A three-state (N=3) automaton where P_2 corresponds to a lower probability of PEV charge request than P_1, and P_3 to a lower probability than P_2. In case of charge urgency (*urg=1)* the state machine will stay at P_1, but if there is no charge urgency by driver's call (*urg=0*), and the power transformer was congested (*cong=1*), i.e. a charge request was denied to avoid transformer overload, the PEV state machine will go to a state with lower probability. If charge urgency was set by the driver (*urg=1)* the state machine will go to P_1 with the highest probability.

III. A Probabilistic Automaton for PEV Charge Management

A. Automaton Design

The problem of managing, in a distributed manner, the individual activity rates (i.e., load) for entities in a large group is similar to the control of active nodes in a wireless sensor network and to the PEV CM problem. For the sensor-network problem, N-state probabilistic automatons have been proposed that are both simple to implement on computationally constrained hardware and require minimal communications for control [24, 27, 28]. Our earlier work, [24] and [28], illustrated the ability of this approach to control participation for a large range of nodes and activities levels in a manner that ensured equity of participation among nodes. For PEV charging, we leverage this automaton design, of which a simple version (N=3) is presented in Fig. 1.

As shown in the state diagram (Fig. 1), if the node (sensor or PEV) is in its middle state, it will transmit during a particular epoch (time period) with probability P_2. In the PEV application, this "transmission" corresponds to the PEV requesting a packet of charge for a fixed length of time (or epoch). If the request can be supported by the infrastructure, the vehicle is allowed to charge for one epoch. In the communications context this would mean being "rewarded" by the channel, through successful transmission of the data. With a successful request, the state machine moves to the next higher probability state (P_1) and transmits during the next epoch with probability $P_1 > P_2$. If the request is not successful, the PEV would not charge for the epoch, would move to the next lower probability state, and would request at the next epoch with probability $P_3 < P_2$. Prior work demonstrated that this automaton approach can adapt to scenarios where the distribution capacity varies over time [29].

For fair and consistent treatment across all PEVs, each user's automaton would have the same design. However, in order to ensure that drivers who need to charge their vehicles more quickly are able to do so, the design can be adjusted to give such vehicles a higher priority. In our design, each charger would have an "urgent" mode [30], which, when selected by the user, increases the probability of charge requests, and also the price of electricity. As implemented in this paper (see Fig. 1) 'urgent' vehicles request charge at each epoch with P_1=1 [31].

B. Possible Implementation Approaches

Key advantages of the proposed packet-based CM approach are that (1) the scheme can be used to manage constraints anywhere in a distribution system, (2) the communication requirements are minimal, and (3) customer privacy is maintained. Here we discuss these advantages by describing possible ways to implement the required communications (broadcast vs. point-to-point communications) and various power system constraints that the algorithm could be used to address.

The packetized method can be implemented to mitigate overloads at a variety of locations within a distribution system, such as avoiding thermal overloads in underground cables, low-voltage service transformers, or medium voltage distribution transformers, or avoiding under-voltage conditions in the network, or (using a hierarchical design) any combination of these constraints. In each case, a charger automaton would communicate with an aggregator responsible for managing a particular constraint. For the case of medium voltage constraints, the aggregator could be located at the distribution substation. For the case of service-transformer constraints, the aggregator would likely be located at the transformer. The only data that would flow from the PEV charger to the aggregator would be charge-packet requests. The aggregator would respond to requests only based on available capacity. In each of these cases, communications could occur over Advanced Metering Infrastructure systems, which typically have very low communications bandwidth and high latencies, emphasizing the importance of a scheme that makes limited use of this bandwidth.

It is possible to implement communications for the packetized method with either one-way (simplex) or two-way (duplex) data flows. In the duplex case, the aggregator would respond to each request individually with either an approval or denial. In the simplex case, the aggregator would broadcast the state of the resource (either overloaded, or not-overloaded) and chargers would make their request locally by merely randomly "listening" to the broadcast signal. The latter version has advantages in terms of privacy, as the transformer is blind to who is receiving permission to charge.

These approaches represent conceptual extremes on how the packetized CM technique could be implemented. Note that combinations of these schemes could be employed simultaneously. For example, a PEV charger might send requests to an aggregator at the substation only if a service transformer's broadcast signal indicated that there was local capacity available. Because vehicle chargers using the packetized method only charge when there is sufficient capacity in the system, our approach ensures that PEV loads will not cause overloads in components that are monitored by the system.

C. Illustrative results for a service transformer

To illustrate the operation of our approach, this section

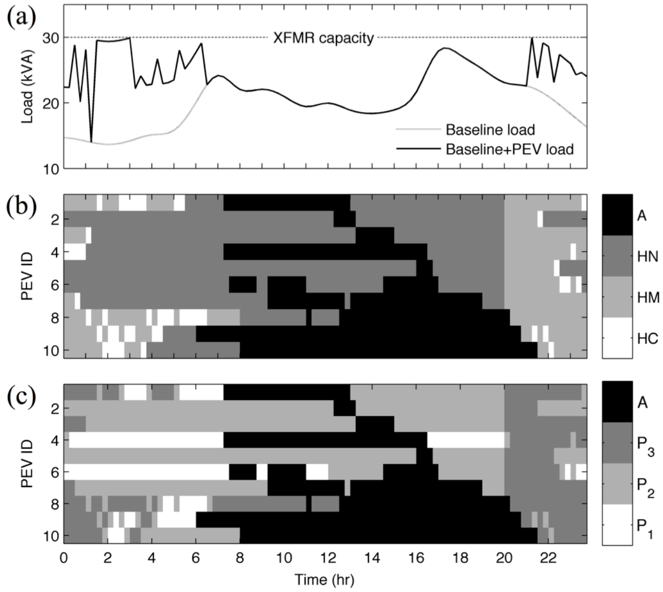

Fig. 2. Illustration of the charge-packet method for a service transformer with a 30kVA limit. (a) Load curve, showing the residential and the aggregate transformer load. (b) PEV status with gray shades indicating: A: PEV is away, HN: PEV is at home but not requesting for charge (either the battery is full, or it is during peak hours), HM: PEV requested a charge packet, but was denied to avoid transformer overload (charge mitigation), HC: PEV is at home and charging. (c) PEV automaton state number with the gray shades showing each automaton's state at the end of the epoch.

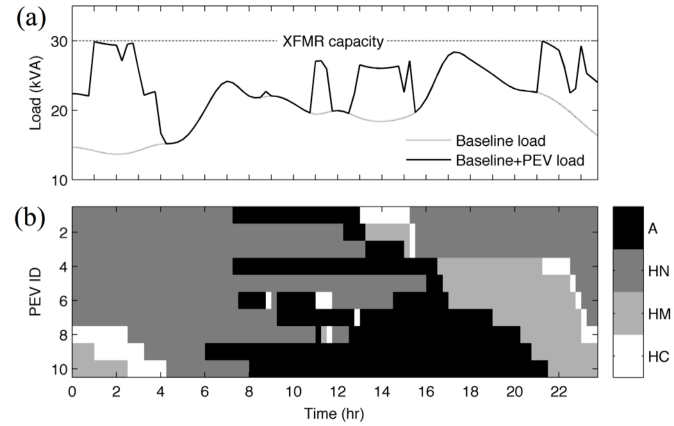

Fig. 3. Sample illustration of the FCFS charging method. (a) Load curve (b) PEV status using the same gray-scale codes as in Fig. 2.

demonstrates how the charge-packet method would operate for the case of a constrained low-voltage service transformer. In this example scenario, a transformer has a peak load limit of 30kVA and serves 20 homes and 10 PEVs. The baseline residential load patterns were the same as used in [2], scaled to an average of 1 kVA per home, with a 0.9 power factor. The PEV travel patterns were randomly sampled from travel survey data [32] for New England, as described in [2]. Each vehicle was assumed to charge using AC Level 2 charging rates (7 kW at 1.0 power factor). The electric vehicle characteristics roughly reflect those of the GM Volt, with an efficiency of 4.46 km/kWh in electric mode and 15.7 km/L in gasoline mode, and a 13 kWh usable battery capacity. While all of the simulation results in this paper are for series Plug-in Hybrid Electric Vehicles (PHEV), the packetized method could just as easily be applied to pure battery electric vehicles (BEV). However, for the BEV case, the travel survey data are likely to be a less accurate representation of travel behavior, since BEV drivers may adjust their travel patterns given the reduced range of the vehicle. For this reason we simulated PHEVs rather than BEVs.

In this paper, we assumed that drivers can decide to choose between urgent or non-urgent charging modes and that, once chosen, this choice is constant during the day (the simulation duration). In the urgent mode, the vehicle requests charge regardless of the price of electricity, and its automaton stays at P_1 (the highest probability). In the non-urgent mode, the vehicle requests charge only during off-peak hours, and its automaton can go to lower states in case of charge denial.

For our first illustrative example, we used the following assumptions. First, all PEVs operate in the non-urgent charging mode, and thus do not request charge during peak hours (8 a.m. to 8 p.m). Second, each PEV charger was managed with a three-state (N=3) automaton as illustrated in Fig. 1, with request probabilities of P_1=1, P_2=0.5 and P_3=0.25. Finally, time epochs were set to 15 minutes.

Fig. 2 shows the simulation result for this example. The top panel shows the transformer load with and without PEV charging. While the load approaches the 30kVA limit, the constraint is satisfied over the entire period. The middle panel shows the status of each PEV over the day, with white bands showing the randomly scattered 15-minute periods during which vehicles were charging (note that vehicles are sorted by the time at which they arrive at home for evening charging). The lower panel shows the changing automaton states over the day, illustrating that during off-peak hours, the automatons are more likely to sit in the lower state (P_3). This is notable since these states are determined locally based only on the success of the vehicle's most recent charge request.

IV. Comparison Charge Management Schemes

The results in Fig. 2 illustrate how the decentralized charge-packet CM approach can be used to keep transformer loads below a desired limit. This section describes two comparison schemes that were used to evaluate and illustrate the relative merits of the packetized approach. As stated in Sec. III, the results that follow assume that all vehicles are series PHEVs, which use gasoline after their batteries are fully depleted.

A. First-come, first-served charge management

A simpler decentralized approach to the CM problem would be a first-come, first-served (FCFS) method in which vehicles are allowed to charge as soon as they arrive home and can continue to charge, so long as there is sufficient capacity available. As we will show, this approach puts vehicles arriving home at a later time at a disadvantage, should there be a capacity constraint in the system. Like the charge-packet method, this approach is largely decentralized, is low in computational complexity, ensures that charging will not exceed the feeder capacity, and can be implemented with equivalent limited communications. In our FCFS implementation, PHEVs are allowed during both peak and off-peak hours. Once charging begins, it continues until one of the following occurs: the battery is fully charged, the PHEV leaves home, or the network (transformer or feeder) becomes overloaded by an increase in non-PHEV load. In the latter case, the system randomly chooses a vehicle to stop charging.

Fig. 3 shows results from the FCFS approach for the same 10-vehicle scenario as in Fig. 2. In this scenario, vehicles have more continuous charging patterns (as seen by the continuity in the white bands in the lower panel). Because time-of-use prices are not considered by PHEVs in this method, they charge regardless of the time of day, as long as the transformer is not overloaded. In this case, vehicles that arrive later in the day or are initially denied charge are at a disadvantage because they cannot start charging until there is sufficient capacity to support additional PHEV charging. As a result PHEVs 9 and 10 do not start charging until the early hours of the morning (Fig. 3(b)). In contrast, the randomized nature of the packetized approach solves this fairness problem by requiring vehicles to request new packets at each epoch, providing vehicles with equal access to the resource, regardless of arrival times. In the packetized simulation (Fig. 2), vehicles 9 and 10 charge during several intervals during the night, with the first packets shortly after vehicle arrival. In Fig. 3, PHEVs 9 and 10 do not get any charge until after 1 and 2 am respectively. The extent to which vehicles get equal access to charging is quantified and compared in Sec. V (see Fig. 7).

The FCFS charging scheme is a useful comparison scheme for two reasons. First, it illustrates how much charging costs increase, if PHEVs are not responsive to time-of-use prices, having the same travel pattern as in packetized charging method. Second, the FCFS method illustrates the potential of the packetized approach to provide equal access to constrained resources for all PHEVs.

B. Optimal Charge Management

The second comparison method is a centralized optimal CM scheme, which we use to identify the minimum cost charge scenario for each travel pattern and compare that cost to that of the packetized case under a two-rate, time-of-use residential tariff. A critical distinction for the optimal case is that the model assumes that PHEV charge rates can be continuously controlled between zero and the full charge rate. Also, and significantly, the travel behavior for each user must be known in advance for the optimization scheme. As in the other cases, all vehicles were assumed to be serial plug-in hybrid electric vehicles, with gasoline used only after the usable battery capacity was expended.

The optimization problem formulation is a mixed integer linear programming model based on the approach in [12]. Only the objective function and our modifications to the model are described here; the reader is referred [12] for further details.

The objective in the optimization method is to minimize the retail costs to vehicle owners associated with traveling the miles described in the travel survey data. Because the vehicles are PHEVs, and the homes are charged for electricity using time-of-using pricing, there are three fuels that can be used for charging: on peak electricity, off peak electricity, or gasoline. The resulting objective (cost) function is given in (1):

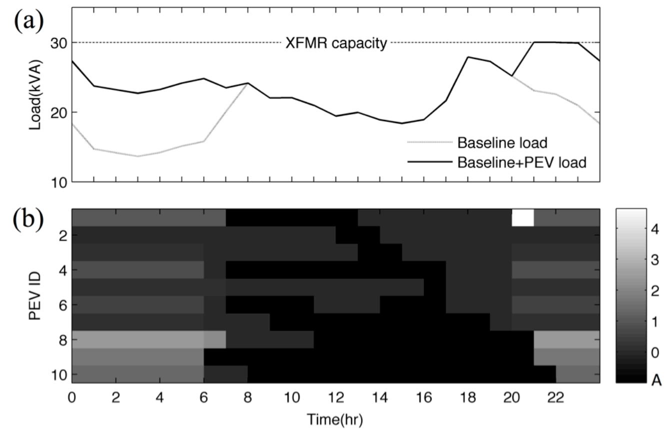

Fig. 4. Illustrative results for optimal charge management. (a) Load curve. (b) PEV status with gray levels showing the amount of energy given to each PEV at each hour. In the grey-level bar, "A" shows the time when the PHEV is away. When at home, hourly charge quantities vary between 0 and 4.64 kWh, which is the maximum quantity delivered in this example.

$$C_t = \sum_{t=1}^{T}\sum_{v=1}^{N}\left[\frac{\pi_e(t)\cdot P(v,t)\cdot h}{\eta_e} + \frac{\pi_g \cdot d_{CS}(v,t)}{\eta_g}\right] \quad (1)$$

where $\pi_e(t)$ and $P(v,t)$ are the price of electricity and the charging power of vehicle v at time *t*; h is the charge epoch length; η_e is the overall efficiency of the charging system ($\eta_e = 0.85$); $\pi_g = 1.06$ \$/L is the price of gasoline; $d_{CS}(v,t)$ is the distance traveled after the battery was depleted (Charge Sustaining, CS mode); $\eta_g = 15.7$ km/L is the CS mode vehicle efficiency; and *T* and *N* are the number of epochs and vehicles, respectively. In our implementation, one-hour epochs were used ($h = 1$), and $P(v,t)$ was a continuous variable that varied between 0 and 7 kW. In order to obtain consistent results, the following two constraints were added to the model in [12]:

$$\sum_{v=1}^{N} P(v,t) + P_r(t) \le \bar{P} \quad \forall t = 1,\dots,T \quad (2)$$

$$\begin{aligned} &P(v,t) \le P(v,t-1) \quad \forall v,t: \\ &d_{tot}(v,t) = d_{tot}(v,t-1) = 0 \;\&\; \pi_e(t) = \pi_e(t-1) \end{aligned} \quad (3)$$

where $P_r(t)$ is the total residential load at time t, $\bar{P}$ is the load limit for the transformer or feeder, and $d_{tot}(v,t)$ is the total distance traveled by vehicle *v* at time *t*. Constraint (2) ensures that the transformer is not overloaded, and (3) forces PHEVs to charge as soon as possible, so long as the total cost is not affected. In other words, if the total distance traveled by PHEV v is zero in two consecutive time slots (if the PHEV is plugged in at home) and the price of electricity is the same at time *t* and *t*-1, the charging power of vehicle *v*'s battery should be greater at the earlier time slot.

Fig. 4 shows results for this optimal charging scheme for the 10-PEV case considered in Figs. 2 and 3. As a result of allowing vehicles to charge at any rate, the approach chooses charge rates that are lower than the full Level 2 rate. This type of "Unidirectional V2G" [5] has advantages in terms of more refined control, but requires additional communication and coordination. As expected, optimal CM fully utilizes the transformer capacity during off-peak hours, but only if travel plans are fully known. The other two methods also keep loads below the power limit, but with somewhat more variability.

V. Results

This section compares the packetized approach to the optimal and FCFS cases, and to variants of the packetized approach, for a larger number of homes and vehicles. Specifically, we simulated a 500 kVA medium voltage transformer serving 320 homes, each with 1 kVA average load. Each home has two vehicles [33] (i.e., 640 vehicles in total), either or both of which could be a PHEV depending on the PHEV penetration level. The number of homes was selected such that the peak residential load was below the transformer's rated load. We assumed that customers were charged for electricity according to a two-rate, time-of-use residential tariff in which the peak (8 a.m. to 8 p.m.) electricity rate is $\pi_e(t)$=\$0.14/kWh and the off-peak rate is $\pi_e(t)$= \$0.10/kWh. These assumed values are representative of (though less extreme than) current retail time-of-use rates in the Northeastern US [34]. For the packetized case, we assumed that vehicles in urgent charging mode were charged the peak price (\$0.14/kWh). It is important to note that this \$0.04 difference between urgent and non-urgent rates is likely conservative, since the cost to utilities of providing non-urgent charging is likely to be only slightly higher than off-peak wholesale energy costs, which are frequently \$0.02-\$0.03/kWh in the Northeastern US [35].

In order to obtain a distribution of outcomes over a variety of likely travel patterns, 100 unique vehicle travel patterns were randomly selected from the survey data (see [2] for details of this Monte-Carlo model).

A. Comparing packetized charging to optimal and FCFS charge management

In this section the packetized approach is compared to results from the FCFS and optimal method for the larger scenario. For the packetized method, we modeled a two-state automaton, with request probabilities of P_1=1 and P_2=0.5. Furthermore, vehicles were set to urgent mode (for the packetized approach) based on the solution from the optimization: if PHEV v charged during peak hours in the optimization results, v was set to urgent charging mode. Essentially this reflects the assumption that drivers were able to estimate their need for urgent charging.

We simulated three different levels of PHEV penetration: 12.5% (N=80), 25% (N=160) and 50% (N=320). Note that these high penetration levels are relatively unlikely in the near term for the aggregate vehicle-fleet in most countries. However, it is not unlikely that some residential neighborhoods could have PEV penetrations that are substantially higher than that of aggregate. As a result of this, and the fact that temporal patterns in non-residential loads differ from residential patterns, we assume that the simulated PHEVs do not impact the two-tier time-of-use price. We also assume that the aggregate system load curve, which would include commercial and industrial customers, is different from the residential load shown in Fig. 5, which shows the baseline

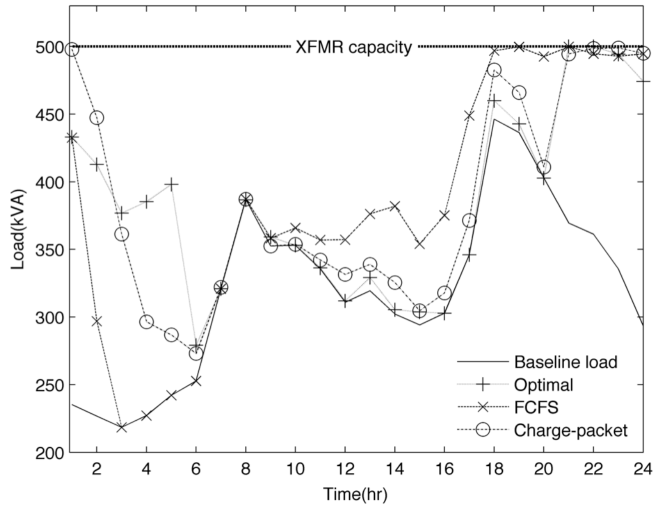

Fig. 5. Daily load curve showing non-PEV residential load and the aggregate load with 25% PHEV penetration.

and total load for 25% PHEV penetration (160 PHEVs) for each CM scheme. In order to make a clear comparison, we chose 1-hour time slots for the FCFS and optimization method, and 1-hour request intervals and packet lengths (i.e., epochs) for the charge-packet method. Fig. 5 shows that the PHEVs in the charge-packet case use slightly more peak hour charging, than in the optimization case, which increases the overall costs for the charge-packet method somewhat. However, the presumption is the unrealistic requirement that the central optimization approach can obtain perfect information about travel plans. What is notable is that the charge-packet scheme keeps loads below the limit, with costs that are nearly optimal as the load presented to the system is adjusted over time and distributed across PEVs in the system.

We compared the average total travel cost per PHEV over 100 one-day Monte Carlo simulations. We assigned each vehicle a random travel pattern from the survey data. The same vehicle-travel pattern combinations were used identically for each scenario, to ensure a fair comparison. The results for two different PEV penetrations (12.5% and 50%), and two different battery capacities are shown in Fig. 6. The gasoline, off-peak and on-peak electricity costs are shown separately. From Fig. 6, we can see that the total travel cost of the charge-packet method is slightly more than that of the optimization method, but much less than the FCFS method. The charge-packet costs are slightly greater because urgency settings were constant during the day, based on the realistic assumption that drivers are not perfect optimizers. The FCFS method is more costly because in this case drivers do not differentiate their charging based on the price of electricity. The result is that in the FCFS method, vehicles consume more peak-hour electricity than in the other methods. One exception is the case of 50% penetration and 24 kWh batteries, where all charging methods use the entire transformer capacity during off-peak hours, but the optimization method can optimally allocate charging to those PEVs that cannot get peak-hour charging. In other charging methods, some PEVs that are not capable of receiving peak electricity (because of not being

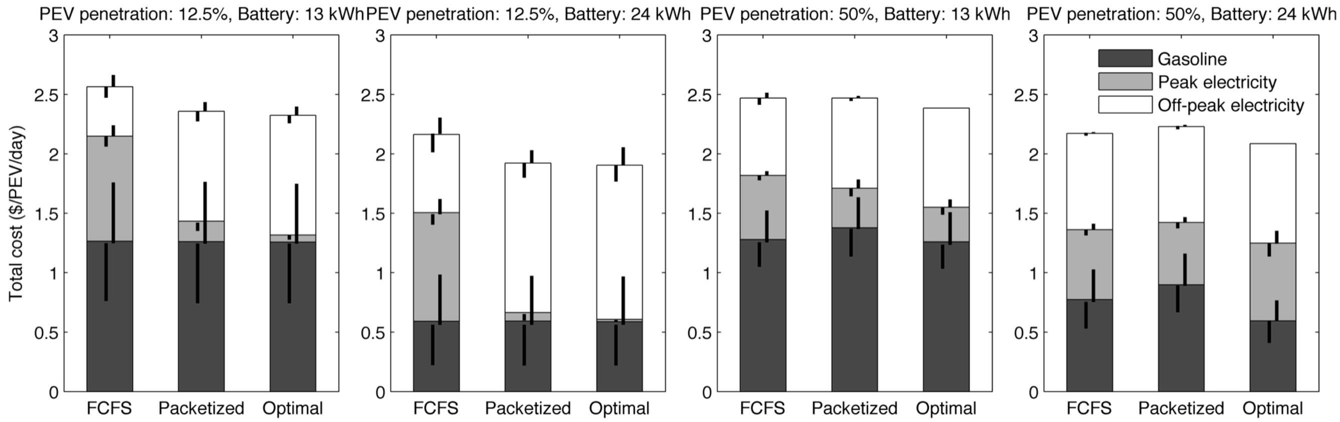

Fig. 6. Average total travel costs in 100 Monte Carlo simulations, showing gasoline, peak and off-peak electricity costs separately in four case studies with different PEV penetrations and battery capacities (bars show the average and black lines show 10th to 50th and 50th to 90th percentile)

home) do not get enough charge overnight, and must use the most expensive fuel, gasoline. It should be noted that in our simulations peak electricity at $0.14/kWh is still cheaper than gasoline in terms of $/km travel.

Generally, in the higher PEV penetration scenarios, there is insufficient off-peak electricity to allow all vehicles to fully charge their batteries, resulting in more peak electricity usage for the optimization and packetized scenarios. Because of this, increased PEV penetrations resulted in a slight increase in travel costs for the optimization and packetized cases. For example, in the 12.5% PEV penetration case, vehicles can use more off-peak electricity than in the 50% PEV penetration case, where peak electricity is used more.

As one would expect, the results indicate that larger battery capacities result in reduced use of the most expensive fuel, gasoline, and thus reduce travel costs. However, the impact of the larger batteries is different in low and high PEV penetration cases. In the low penetration case, more off-peak electricity can be used for the larger battery as more transformer capacity is available; in the high penetration case, the transformer capacity is exhausted for both the 13 kWh and 24 kWh battery cases during the off-peak hours, making the benefits of larger batteries less clear.

Most importantly, these results show that the cost of using the packetized method is only 0.9% to 5.2% greater than what we found for the optimal CM case (as opposed to 3.1% to 14.1% for the FCFS CM scheme). The charge-packet method requires much less information from the PEV owner (only the choice of an urgency setting) and requires far less two-way communication than would be required to implement centralized optimization method. In summary, we find that the charge-packet method can achieve near optimal costs, while preserving driver privacy and being robust to random changes in travel behavior.

B. Comparing variants of the charge-packet method

The automaton used in the packetized PEV charger allows PEV charging to adapt to reduce the impact on the distribution system, such as overloaded transformers or feeders. However, different automaton probabilities and structures will change the performance of the charge-packet method, particularly with respect to the burden on the communications infrastructure. To investigate the performance of the charge-packet method, we introduced the idea of differentiating between charge-packet lengths, i.e., the time epoch a PEV is given permission to charge, and request intervals, i.e., the time epoch between two requests for charge.

We simulated the charge-packet method with different automaton probabilities, packet lengths (5-minute and one-hour), and request intervals (5-minute and one-hour). The results were compared across three metrics: (1) average total cost, (2) a measure of the extent to which the method provided each vehicle with equal access to the charging resources, and (3) the number of messages transmitted by the PEVs or the transformer, per vehicle-day, assuming the bi-directional communication (duplex) case is implemented (see Sec. III.B).

One of the problems observed with the FCFS charging case (Sec. IV.A) was that vehicles that began charging earlier than others, before a period in which charge mitigation occurred (typically early evening hours), were not required to stop charging when new vehicles arrived. As a result, vehicles that arrived later in the day frequently were not allowed to begin charging until capacity in the system was released, effectively giving them “less equal” access to charging resources. In order to measure the extent to which vehicles were given equal access to grid resources under different scenarios, we defined an Equal Access Metric (EAM) to assess the “fairness” of each method. For this purpose, we find the probability of charge mitigation for each vehicle v, $P_M(v)$, by dividing the number of time slots that the PEV charge request is denied by total number of time slots that the PEV is requesting charge from the transformer. P_M was computed only for off-peak hours, when all vehicles were requesting charge. Given the standard deviation of $P_M(v)$ over all v, $\sigma(P_M)$, EAM was calculated as follows:

$$EAM = 1 - \sigma(P_M). \tag{4}$$

$\sigma(P_M)$ ranges between 0 and 1, which means that EAM has the same range. Therefore, a method with perfectly equal access will have EAM = 1, and lower values of EAM indicate that

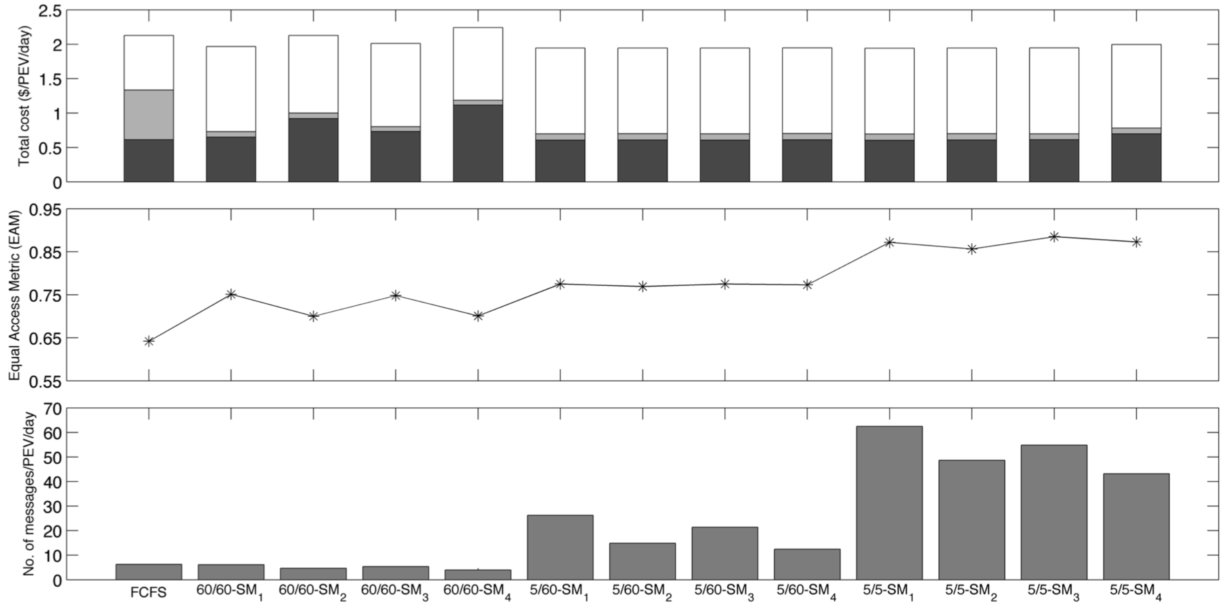

Fig. 7. Comparison of FCFS charging and variations of the charge-packet method. (Top) Average total costs over 100 Monte Carlo simulations, with shades indicating gasoline (black), peak (gray) and off-peak (white) electricity costs. (Middle) The extent which consumers have equal access to the available capacity. (Bottom) Communication burden for the various methods. t_1 and t_2 in t_1/t_2 (e.g., 60/60) show the request interval and the packet length in minutes, respectively. See the text for definitions of the state-machine probabilities SM_i.

some vehicles are given more access than others. The rationale for this metric is that as long as all the PEVs are mitigated with the same probability (i.e., the same ratio of mitigation to total requests) the method maintains its fairness.

Communication burden was measured by counting the number of messages exchanged over the communications network per vehicle per day. Following the two-way communication system design, we assumed that each charge packet request requires one message submission to the aggregator. If the PEV gets a reply (one message), this means that the request is approved; otherwise the charge request is denied.

Fig. 7 shows these three metrics, for three different charge time-interval combinations and four different state machines, along with results for the FCFS charging method. Time-interval combinations are defined using the notation t_1/t_2, in which t_1 is the interval of times between requests and t_2 is the length of the charge packet, both in minutes. The three time-interval combinations compared were 60/60, 5/60 and 5/5, and the state machines were SM$_1$: $\{P_1 = 1, P_2 = 0.5\}$, SM$_2$: $\{P_1 = 1, P_2 = 0.5, P_3 = 0.25\}$, SM$_3$: $\{P_1 = 0.8, P_2 = 0.4\}$ and SM$_4$: $\{P_1 = 0.8, P_2 = 0.4, P_3 = 0.2\}$. As expected, smaller request intervals and charge-packet lengths reduced charging costs, but increased communication costs. The 5/60 gives about the same travel cost as 5/5, but at the expense of fairness (reduced EAM). It is possible that excessively frequent on/off cycles could have adverse effects on the battery or charging systems. If this was the case, the 5/60 method could be preferable, given that the increase in cost is negligible. Note that 5/60 outperforms 60/60 in terms of equal access.

The results also suggest that using state-machines with N=3 rather than N=2 states, or with lower transition probabilities, can substantially reduce the burden of CM on the communications system. This notion agrees with the results obtained previously for automaton control applied to wireless sensor node participation [24]. However, these changes also result in small increases in travel costs. If communications bandwidth is not a constraint, the 5/5 charge-packet is superior in terms of both total cost and equal access.

VI. Conclusions

This paper draws similarities between the problem of managing the charging of electric vehicles and that of providing multiple devices with access to a bandwidth-constrained communications channel. We propose to treat PEV charging as a random access problem where charge is delivered through many 'charge-packets'. As with random access communication channels, the packetization of charge allows distribution system objectives (i.e., efficient use of available resources without overloading the network) and customer objectives (reducing travel costs) to be achieved simultaneously. Leveraging this approach, this paper presents a new decentralized, automaton-based charge management strategy, which preserves users' privacy more than many existing charge management schemes. Simulations of packetized charging in a constrained residential distribution feeder indicate that the cost increase of our method over an omniscient centralized optimization method (which is untenable in its information requirements) is only 0.9% to 5.2%. However, in comparison to the optimal approach, the charge-packet technique can be implemented with first-generation low-bandwidth advanced metering infrastructure.

While the simulations in this paper are for plug-in hybrid electric vehicles charging in a residential distribution network, the packetized method could be adapted and applied to other thermal or battery storage loads. Battery electric vehicles are likely to have somewhat different charging and travel characteristics than PHEVs: BEV owners would probably take fewer very long trips, and are likely to request the "urgent" charging mode more frequently. Similarly, the method could be adapted to the management of thermal loads, such as HVAC and water heating. Future work will investigate these adaptations.

Finally, it is important to note that the charge packet approach would not be desirable if discrete switching caused substantially accelerated battery degradation. While detailed analysis of battery impacts are beyond the scope of this paper, evidence from prior research suggest that charging Lithium Ion batteries at a constant rate resulted in no aging benefit, relative to a variable changing rate [36], and that pulsed charging can, under some circumstances, be beneficial to battery life [37].

VII. References

[1] Q. Gong, S. Midlam-Mohler, V. Marano, G. Rizzoni, "Study of PEV Charging on Residential Distribution Transformer Life," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp.404-412, Mar. 2012.

[2] A. Hilshey, P. Hines, P. Rezaei, J. Dowds, "Estimating the Impact of Electric Vehicle Smart Charging on Distribution Transformer Aging," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp.905-913, Jun. 2013.

[3] J. Sears, J. Dowds, L. Aultman-Hall, P. Hines, "Travel Demand and Charging Capacity for Electric Vehicles in Rural States: A Vermont Case Study," *Transportation Research Record*, (in press), 2012.

[4] Society of Automotive Engineers, "SAE charging configurations and ratings terminology," *SAEJ1772,* 2011.

[5] E. Sortomme, M.A. El-Sharkawi, "Optimal Combined Bidding of Vehicle-to-Grid Ancillary Services," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp.70-79, Mar. 2012.

[6] C. Quinn, D. Zimmerle, T.H. Bradley, "An Evaluation of State-of-Charge Limitations and Actuation Signal Energy Content on Plug-in Hybrid Electric Vehicle, Vehicle-to-Grid Reliability, and Economics," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp.483-491, Mar. 2012.

[7] K. Clement-Nyns, E. Haesen, J. Driesen, "The Impact of Charging Plug-In Hybrid Electric Vehicles on a Residential Distribution Grid," *IEEE Trans. Power Syst*., vol. 25, no. 1, pp.371-380, Feb. 2010.

[8] S. Deilami, A.S. Masoum, P.S. Moses, M.A.S. Masoum, "Real-Time Coordination of Plug-In Electric Vehicle Charging in Smart Grids to Minimize Power Losses and Improve Voltage Profile," *IEEE Trans. Smart Grid*, vol. 2, no. 3, pp.456-467, Sept. 2011.

[9] E. Sortomme, M.M. Hindi, S.D.J. MacPherson, S.S. Venkata, "Coordinated Charging of Plug-In Hybrid Electric Vehicles to Minimize Distribution System Losses," *IEEE Trans. Smart Grid*, vol. 2, no. 1, pp.198-205, Mar. 2011.

[10] R.A. Verzijlbergh *et al.*, "Network Impacts and Cost Savings of Controlled EV Charging," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp.1203-1212, Sep. 2012.

[11] P. Richardson, D. Flynn, A. Keane, "Optimal Charging of Electric Vehicles in Low-Voltage Distribution Systems," *IEEE Trans. Power Syst*., vol. 27, no. 1, pp.268-279, Feb. 2012.

[12] R. Sioshansi, "Modeling the Impacts of Electricity Tariffs on Plug-in Hybrid Electric Vehicle Charging, Costs, and Emissions," *Operations Research*, vol. 60, no. 3, pp.506-516, May-June, 2012.

[13] C. Ahn, C. Li, H. Peng, "Optimal Decentralized Charging Control Algorithm of the Electrified Vehicles Connected to Smart Grid," *Journal of Power Sources*, vol. 196, no. 23, pp.10369-10379, Dec. 2011.

[14] M. C.W. Kintner-Meyer, "Smart Charger Technology for Customer Convenience and Grid Reliability," in *Proc. 24th Electric Vehicle Symp.*, Stavanger, Norway, 2009.

[15] P. Richardson, D. Flynn, A. Keane, "Local Versus Centralized Charging Strategies for Electric Vehicles in Low Voltage Distribution Systems," *IEEE Trans. Smart Grid*, vol.3, no.2, pp.1020-1028, June 2012.

[16] H. Yifeng, B. Venkatesh, G. Ling, "Optimal Scheduling for Charging and Discharging of Electric Vehicles," *IEEE Trans. Smart Grid*, vol.3, no.3, pp.1095-1105, Sept. 2012.

[17] Di Wu, D.C. Aliprantis, L. Ying, "Load Scheduling and Dispatch for Aggregators of Plug-In Electric Vehicles," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp.368-376, Mar. 2012.

[18] N. Rotering, M. Ilic, "Optimal Charge Control of Plug-In Hybrid Electric Vehicles in Deregulated Electricity Markets," *IEEE Trans. Power Syst*., vol. 26, no. 3, pp.1021-1029, Aug. 2011.

[19] Z. Ma, D. S. Callaway, and I. A. Hiskens, "Decentralized charging control of large populations of plug-in electric vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 21, no. 1, pp.67,78, Jan. 2013.

[20] M.D. Galus *et al.*, "Integrating Power Systems, Transport Systems and Vehicle Technology for Electric Mobility Impact Assessment and Efficient Control," *IEEE Trans. Smart Grid,* vol.3, no.2, pp.934-949, June 2012.

[21] K. Kok *et al.*, "Dynamic pricing by scalable energy management systems - Field experiences and simulation results using PowerMatcher," in *Proc. IEEE Power and Energy Society General Meeting,* San Diego, CA, 2012.

[22] B. Alexander, "Dynamic Pricing? Not So Fast! A Residential Consumer Perspective," *The Electricity Journal*, vol. 23, no. 6, pp.39-49, 2012.

[23] A. Brooks *et al.* "Demand dispatch," *IEEE Power & Energy Mag*., vol. 8, no. 3, pp. 20–29, May/Jun 2010.

[24] J. Kay and J. Frolik, "An expedient wireless sensor automation with system scalability and efficiency benefits," *IEEE Trans. Syst. Man Cybern. A., Syst. Humans*, vol. 38, no. 6, pp.1198 - 1209, Nov. 2008.

[25] F. Zhong, "A Distributed Demand Response Algorithm and Its Application to PHEV Charging in Smart Grids," *IEEE Trans. Smart Grid*, vol.3, no.3, pp.1280-1290, Sept. 2012.

[26] T. Rappaport, *Wireless Communications: Principles and Practice, 2nd ed.*: Prentice Hall, 2002.

[27] R. Iyer and L. Kleinrock, "QoS control for sensor networks," in *Proc. IEEE ICC*, Anchorage, AK, 2003, pp.517–521.

[28] J. Frolik, "QoS control for random access wireless sensor networks," in *2004 Wireless Communications and Networking Conference (WCNC04)*, Atlanta, GA, 2004.

[29] J. Frolik and P. Hines, "Random access, electric vehicle charge management," in *Proc. 1st IEEE International Electric Vehicle Conf.*, Greenville, SC, March 4-8, 2012.

[30] J. Frolik and P. Hines, "Urgency-driven, plug-in electric vehicle charging," in *Proc. IEEE PES Innovative Smart Grid Technol. (ISGT) Europe Conf.*, Berlin, Germany, 2012.

[31] A. Hilshey, P. Rezaei, P. Hines, J. Frolik, "Electric vehicle charging: Transformer impacts and smart, decentralized solutions," in *Proc. IEEE Power & Energy Society General Meeting*, San Diego, CA, 2012.

[32] U.S. Dept. Transportation, Federal Highway Administration (2009). *National Household Travel Survey (NHTS)* [Online]. Available: http://nhts.ornl.gov/download.shtml.

[33] S. Shengnan, M. Pipattanasomporn, S. Rahman, "Challenges of PHEV penetration to the residential distribution network," in *Proc. IEEE Power & Energy Society General Meeting*, Calgary, Canada, 2009.

[34] Green Mountain Power, "GMP Rates," Online: http://www.greenmountainpower.com/customers/payment/gmp-rates/, Aug. 8, 2013.

[35] ISO New England, "Markets," Online: http://www.iso-ne.com/markets/, Aug. 8, 2013.

[36] Elena Marie Krieger, "Effects of variability and rate on battery charge storage and lifespan", " Ph.D. dissertation, Dept. Elect. Eng., Princeton Univ., Princeton, NJ, 2013.

[37] L.R. Chen, S.L. Wu, D.T. Shieh, and T.R. Chen. Sinusoidal ripple current charging strategy and optimal charging frequency for Li-ion batteries. IEEE Trans. Ind. Electron., 60(1):88{97, 2013.

VIII. Biographies

Pooya Rezaei (S‘12) received the M.Sc. degree in Electrical Engineering from Sharif University of Technology, Tehran, Iran in 2010, and the B.Sc. degree in Electrical Engineering from University of Tehran, Tehran, Iran in 2008.

Currently, he is pursuing the Ph.D. degree in Electrical Engineering at University of Vermont.

Jeff Frolik (S'85, M'95, SM'11) received the B.S.E.E. degree from the University of South Alabama in 1986, the M.S.E.E. degree from the University of Southern California in 1988 and the Ph.D. degree in Electrical Engineering Systems from the University of Michigan in 1995. He is an Associate Professor in the School of Engineering at University of Vermont.

Paul D. H. Hines (S'96, M'07) received the Ph.D. in Engineering and Public Policy from Carnegie Mellon U. in 2007 and M.S. (2001) and B.S. (1997) degrees in Electrical Engineering from the U. of Washington and Seattle Pacific U., respectively.

He is currently an Assistant Professor in the School of Engineering at the U. of Vermont, and a member of the adjunct research faculty at the Carnegie Mellon Electricity Industry Center.