Urgency-Driven, Plug-In Electric Vehicle Charging

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Abstract— **In this work, we propose a strategy for managing the charging of plug-in electric vehicles (PEVs) that simultaneously avoids overloads and provides demand-based allocation of power distribution resources. The strategy leverages (1) a 'power packet' approach which allocates charging for finite lengths of time and (2) a locally defined automaton where a user's 'urgency' sets the request rate for charging. The charge management strategy requires very little communications between the PEV charger and the power distribution system. Furthermore, the system's charge manager is blind to which PEV is making the request thereby ensuring fairness and privacy. The work details possible implementations of the approach and illustrates the methodology through simulations.**

Keywords- plug-in electric vehicles, load management, media access control, battery charging

I. INTRODUCTION

Plug-in electric vehicles (PEVs) are touted to have numerous societal benefits including the promise to reduce an individual's dependency on liquid fossil fuels for transportation. Charging of personal PEVs is envisioned to occur at workplaces, shopping centers, etc., where the power delivery infrastructure is already sufficient to support commercial endeavors [1]. However, it is more likely that an individual will primarily charge their PEV at home thereby impacting residential distribution networks, which are often more constrained, in addition to impacts on the grid as a whole. At the local level, transformers, substations and underground cables can age rapidly if operated beyond their specified thermal limits due to the additional power draw by PEV chargers [2].

The authors have recently proposed an automaton-based approach for PEV charge management [3], leveraged from the domain of wireless sensor networks [4] and random access communication channels (e.g., ALOHA and CSMA [5]), in order to avoid the aforementioned detrimental effects on the distribution infrastructure. This approach also demonstrated fairness and anonymity that we contend is desirable in a charge management scheme. That approach was shown to be simple and robust, under supply constraints, in controlling the number of PEVs charging at any time. Fundamental to this approach is that PEV charging is conducted via *power packets*; that is, over many (e.g., 100s of) discrete time intervals (e.g., 5-15 minutes) and that any particular customer must request each and every packet. This packetized approach ensures that all PEVs regularly compete for charge capacity, which is especially important in order to maintain equal access to the supply resources under conditions where the distribution system capacity becomes constrained.

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In our previous work we assumed that, even if customers had different charge needs, they had the same 'urgency' to receive their charging and there was no price (dis)incentive to charging. These assumptions, however, are not consistent with proposed dynamic pricing schemes geared toward mitigating detrimental effects of PEV charging (e.g., [6]). Initial consideration of user 'urgency' was presented recently [7]. In that work, we found that 'urgency' can be readily incorporated in the probabilistic automaton based approach. Herein, we expand upon that nascent effort and consider various demand-driven charge scenarios.

The method proposed in this paper has similar goals, but differs substantially in implementation from optimization or price-based solutions to the charge management problem. Optimization-based methods (e.g., [10], [11]) require that vehicle owners submit substantial amounts of information to grid operators. While this can lead to globally optimal solutions, privacy concerns arise when electricity consumers are required to declare willingness to pay, arrival and departure times, etc. to grid operators. Methods that require real-time-pricing have been proposed (e.g., [12]), but these require fairly complicated retail tariffs, which many utilities have been reluctant to deploy due to concerns from the public about such rates. The 'power packet' method, on the other hand, requires that utilities set up a retail tariff for electric vehicle smart charging with different rates for "urgent" and "standard" charging modes, which could be selected by the user with a simple switch at the charging station. This information does not need to be transmitted to the utility, other than for billing purposes (which can be handled at the meter itself), reducing privacy concerns (see Sec. II).

This work is organized as follows. First we review the 'power packet' approach to PEV charge management. We present different automaton designs that accommodate customer 'urgency'. In each case, the customer's PEV charge request activity would be proportional to the price one is willing to pay for charging. Finally, we illustrate through simulation the effectiveness of these approaches in managing charge demand and in utilizing the capacity effectively. A key advantage of the proposed approach is that the power distribution system is blind to the vehicle from which the charge requests are being made and thus anonymity/privacy of customers is maintained. The management approach is simply to determine whether capacity in the systems exists, or not. The individual users, through their automatons, manage/adjust their behavior accordingly.

II. Probabilistic Automaton

The automaton-based approach, first proposed in [3], for PEV charge management recognized that both PEV needs and the system's capacity are dynamic, random quantities. As such, managing the charging of each PEV according to a predetermined schedule would require significant coordination and communications. This communication would necessarily involve detailed customer information and thus create possible security/privacy issues. Alternatively, the probabilistic automaton approach has each PEV charger locally determine whether to request a charge during any particular time interval (i.e., an epoch). The probability of that request is dictated by the state of the automaton. Automatons are managed through a broadcast response by a centralized charge manager (nominally located at the distribution station).

The *N*-state probabilistic automaton design we are leveraging herein was originally developed for managing nodes in a wireless sensor network [4, 8]. In that work, the design showed the ability control participation of random autonomous agents over a wide range of values. A simple version ($N = 3$) of that automaton is shown in Fig. 1. For our applications, if the PEV charger is in the highest state (i.e., right-most state in Fig. 1), it will transmit a charge request during the current epoch with probability *1*. If the request is successful and therefore rewarded by the charge manager, the PEV will be charged for the duration of the packet and the automaton will stay in that highest state and request a charge again in following epoch. Alternatively, if there is insufficient capacity in the distribution system to support additional charging, the PEV's request will be denied and its automaton will move to a lower state (which reduces the probability of a request occurring in the subsequent epoch to p).

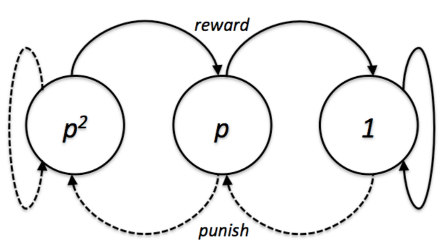

Fig. 1. Three-state automaton where p is the probability of charge request during an epoch and is proportional to the 'urgency' set by the PEV owner. Solid lines indicate state changes when automaton is 'rewarded'; dotted lines are state changes associated with 'punishments'.

As a result of this approach, each PEV requests charge independently every epoch based on the probability associated with its current state (e.g., 1, p, p^2 for the automaton in Fig. 1). The charge manager does not track which PEV is requesting charge or the state of any particular PEV's automaton. All requests are treated equally and PEVs adjust their state autonomously based only on the feedback provided by the charge manager.

This automaton can be readily adapted to dynamic retail electricity tariffs. Notionally, a customer has a certain 'urgency' to complete a charge over a fixed amount of time. This urgency may be tied to the price the customer is willing to pay for charging. If this premise is accepted, then there are two (if not more) ways to leverage it for PEV charge management, under the power packet approach.

One approach is to allow the user to set their PEV charger in either "urgent" or "standard" modes. This could establish a price threshold at which charging will no longer be requested. The higher the urgency, the higher is this price threshold. In our automaton design, the current price can influence the state at which the automation is in. A second approach, which admittedly has not be explored as a policy, is that users pay for the right to request charge. That is, the state of the user's automaton probability dictates the price paid for every met charge request. Urgent users may set their automaton probability (in Fig. 1) to $p = 1$ knowing that they will be requesting charge more frequently and thus be receiving power packets more quickly. A less urgent user may set their urgency lower (e.g., $p = 0.5$) and on average will request at half the rate. Should this user's request be accepted, the power packet would be received at a lower cost than for the first user. However, if charging were denied due to capacity issues, the PEV would be punished thus moving it to a lower state (e.g., $p^2 = 0.25$) and thereby reducing its request rate. This approach will result in less-urgent customers having a lower overall probability of completing charge than more-urgent customers. That being said, for the same amount of charge, the less-urgent customer pays a lower price.

In both approaches, the customer has control over what price they are willing to pay to meet their charging needs. To implement these approaches, the charge manager will simply need to determine and present to all customers either a price-per-packet or a price-per-request rate. Based on price thresholds established by the customer, an automaton can be developed that reflects their urgency to charge. That is, the request probability will increase with urgency and will be reflected by increasing the values loaded in the automaton's states (i.e., p in Fig. 1).

III. Examples

To illustrate the proposed method, we present simple and readily scalable examples in which the charging of 100 PEVs needs to be managed. For sake of illustration, we assume Level-1 home charging for these vehicles and that completing a full charge (0-100%) takes 10 hours [9]. We consider three cases more to illustrate the flexibility and robustness of the approach than to provide specific performance numbers. Table I summarizes our simulation parameters. For each of these examples we assume each PEV can receive a full 10-hour charge (i.e., 120, 5-minute power packets).

The first two cases consider the same supply profile (Fig. 2) that initially accommodates all vehicles but becomes increasingly limited. To illustrate the approach we assume that 100 PEVs are connected to a feeder that has variable amount of power that can be allocated for charging (up to 192 kW).

TABLE I SIMULATION PARAMETERS FOR PEV CHARGING

Parameter	Value
Charge need per PEV	10 hours (full charge – Level 1)
Power packet duration	5 minutes
Case 1	All PEVs at urgency 1.0; charge window 10 hours
Case 2	PEV urgency evenly distributed between 0.2, 0.4, 0.6, 0.8 and 1.0; charge window of 10 hours.
Case 3	Urgency profile of *Case 2*; charge window is extended to 12.5 hours providing additional capacity

There is a constant demand of 12,000 (120 charge intervals/PEV x 100 PEVs) power packets in these cases but with a charge window of only 10 hours the overall the capacity is 80% of that need (i.e., 9,600 power packets). For the last case, the profile is similar but the overall window length is 12.5 hours resulting in a full 12,000 power packets being available. The objectives of the management scheme are to (1) provide priority charging for those customers willing to pay the upcharge and (2) ensure all the system capacity is indeed used even if customers are stating low urgency.

A. *Case 1: Fixed urgency, Variable capacity*

For *Case 1*, we consider a worst-case scenario where all 100 PEVs require the maximum 10 hours (i.e., each PEV requires 120, 5-minute power packets) and all users have maximum urgency (i.e., $p = 1$ in Fig. 1). Clearly this case will not accommodate all users fully. In fact, for the charge manager to be fair, it should not accommodate any customer fully. Fig. 3 illustrates the random access approach achieved through using the proposed approach. As illustrated, on average each PEV receives 80% of its required charge and the system's capacity, albeit constrained, is fully utilized.

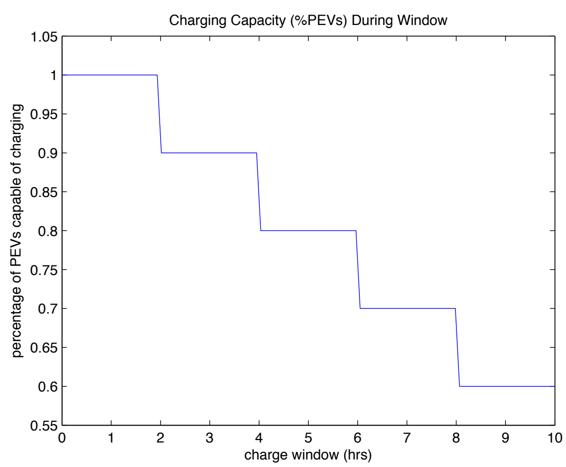

Fig. 2. Distribution system capacity in terms of percentage of 100 PEVs charging over the simulated 10-hour charge window.

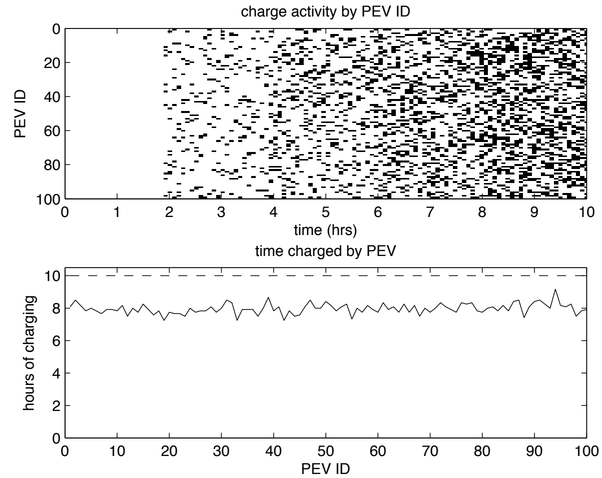

Fig. 3. Top: Charge activity over the 10-hour window by PEV ID. The system can initially serve all PEVs ("charging" indicated in white). As the feeder becomes constrained, all PEVs have reduced and random access to charging. Black indicates "not charging". Bottom: Charging completed by PEV over the 10-hour window. For this example, the overall charging achieved was 100% of available capacity without *a priori* scheduling and on average (across PEVs) 80% of the charge requested.

B. *Case 2: Variable urgency, Variable capacity*

In *Case 2*, we consider the scenario where different users assign different urgency to the day's charging. A low-urgency customer may is willing to pay only the lowest rate for the received power and as a result be willing to take less than a full charge. In contrast, the highest-urgency customer is always willing to take a charge regardless of price. We implement this dichotomy through the automaton shown in Fig. 4 using the parameters presented in Table 2. Using the previous capacity profile (Fig. 2), we find that the automaton approach indeed meets our objectives. Specifically, we see (by the white band at the top of Fig. 5) those PEVs (ID No. 1-20) with highest urgency ($p = 1$) nearly all receive full charge. Through the completely uncoordinated accessing of the power distribution system, the approach manages to proportionally allocate the capacity by urgency as illustrated in Table 2.

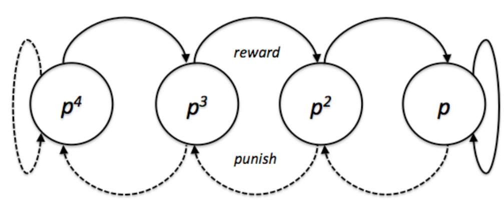

Fig. 4. Four-state automaton used for Case 2 study. *p* correspond to customer's urgency.

While the automaton used in *Case 2* (Fig. 4) achieves the expected results, it has the downside of not effectively utilizing the available capacity in the system. As many PEVs were set to have low urgency (e.g., 0.2 or 0.4) the frequency of their charge requests were such that the overall utilization of the available capacity was only ~60 % in this experiment. As such, we are motivated to consider an alternative automaton that provides both priority and effective resource utilization.

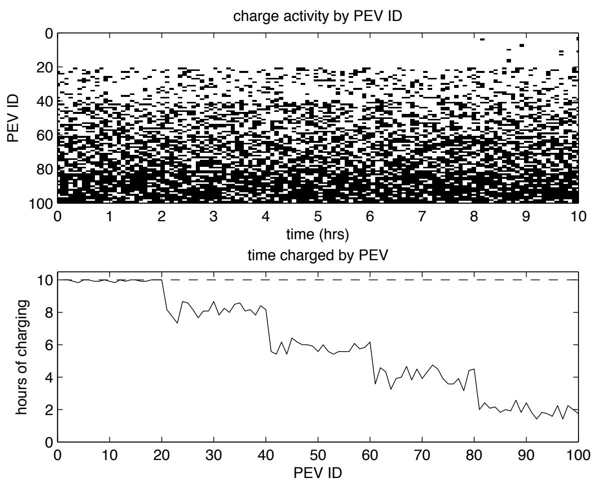

Fig. 5. Top: Charge activity over the 10-hour window by PEV ID for *Case 2* where PEVs have different 'urgency'. Most urgent customers receive a power packet nearly every epoch to fully meet their need. Less urgent customers (ID > 20) share the capacity. Bottom: Charging completed by PEV over the 10-hour window.

TABLE II SIMULATION PARAMETERS FOR PEV CHARGING

PEV ID	Urgency	Power packets received	Mean % completed	Deviation %
1-20	$p = 1.0$	118-120	99.5 %	0.6 %
21-40	$p = 0.8$	88-104	81.5 %	3.6 %
31-60	$p = 0.6$	67-74	58.1 %	3.0 %
61-80	$p = 0.4$	38-57	40.6 %	4.7 %
81-100	$p = 0.2$	17-29	19.7 %	3.2 %

C. *Case 3: Variable urgency, Sufficient capacity*

In *Case 3*, we consider perhaps a more realistic case where there is sufficient capacity in the system but there is a desire to prioritize the charging among users (again, by a customer's willingness to pay for that level of service). As seen in *Case 2*, that automaton enabled priority but not the efficient use of the capacity. In this experiment, we allow even the lowest-urgency users to achieve a state where they will request a charge during an epoch with certainty (Fig. 6).

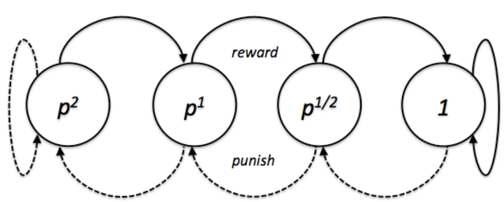

Fig. 6. Four-state automaton used for Case 3 study. By allowing low-urgency customers the ability to reach a $p = 1$ state improves overall utilization of the distribution system capacity.

We repeat the aforementioned experiment with increasing the charge window to 12.5 hours. This provides a capacity equal to the full PEV demand (i.e., 12,000 power packets). Our results are seen in Fig. 7.

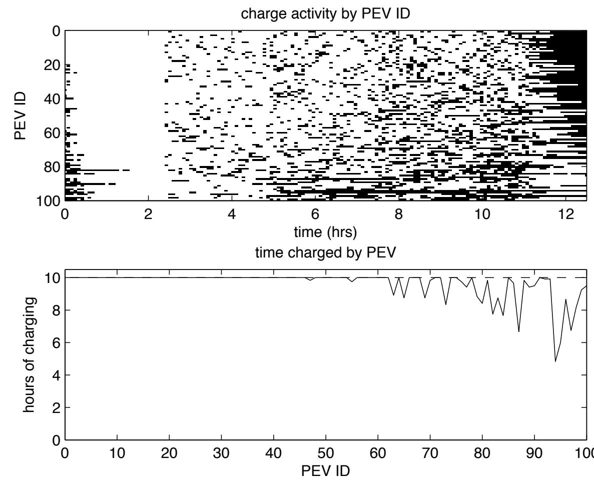

Fig. 7. Top: Charge activity over the 12.5-hour window by PEV ID. Bottom: High-urgency PEVs received full 10-hour charge.

Ideally, we would see PEVs No. 1-20 charge continuously for the first 10 hours (as they have the highest urgency) and then the remainder of the PEVs complete their charge in order of remaining urgency (i.e., 0.8 to 0.2). However, that would require coordination between the charge manager and the individual PEV chargers that, as we noted at the onset, was not desirable. From our results we do see from Fig. 7-top that all high-urgency PEVs complete their charge in about 11 hours. Furthermore, we see that all PEVs with urgency greater than 0.6 receive effectively a full 10 hours of charging. Only the lowest-urgency PEVs do not complete full charging even though there was capacity were it to be ideally managed. Overall in this experiment, the capacity was 96.2% utilized; again, without any specific coordination by the charge manager, unique identification of individual customers, etc.

IV. CONCLUSION

Leveraging a recently proposed approach using probabilistic automatons [3, 7], this paper shows that it is feasible to manage the charging of plug-in electric vehicles in a residential distribution system using customer 'urgency' as a means to accommodate dynamic pricing models. For demonstration purposes, the automatons presented herein have been of simplistic design to accommodate the trade-off between the needs of high-urgency customers and enabling low-urgency customers to take advantage of excess capacity. Based on our wireless sensor network work [8], we expect that through further analyses of the state probabilities will lead to improvements in this tradeoff. Another advantage of the proposed approach is that it can easily be adapted to minimize the amount of bandwidth required for communications between the power grid and electric vehicles. This should make smart charging feasible in within the context of low bandwidth and high latency communications systems that are common in current Advanced Metering Infrastructure (AMI) systems.

V. References

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VI. Biographies

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