DIRECT LOAD MANAGEMENT OF ELECTRIC VEHICLES

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ABSTRACT

Electrical Vehicles are gaining increasing attention, due to the opportunities and challenges they present for the energy market. On the one hand, they will allow to drastically reduce the need for oil; on the other hand they may require a significant shift in the day to day management of the electricity generation. This paper is concerned with finding appropriate models for residential load in light of a widespread penetration of electric vehicles. The analysis is aimed at finding a SmartGrid solution that would enable us to optimize the generation dispatch in real time and allow to plug cars in any SmartGrid enabled plug. The key idea is to discriminate between regular load and the load due to the EVs, gathering in real time aggregate information about the sensed EV arrivals and their associated charging times in a demand matrix, that can be readily used to optimize the dispatch, while updating without real time constraints the billing record for the EV.

Index Terms— Electric Vehicles, Load Forecast, Direct Load Control, Optimization, Communication

1. PROBLEM STATEMENT AND BACKGROUND

Excitement is growing everyday as the beginning of the green car revolution is getting closer [1]. Electric vehicles (EV) will be entering the market later this year. EVs produce few or no emissions and allow to reduce the dependency on foreign oil imports. While this is an enticing future to look forward to, the main technical concern with the practicality of this idea is if the grid can support the widespread adoption of EVs. In fact, like in other networks, the distribution of energy is limited by congestion, which manifests itself in two ways: through a limited generation capacity and through the necessity of not overloading the transmission lines. Thus, the challenge is to dispatch sufficient energy to meet the load while avoiding congestion. To do so, the control algorithm needs to predict the load with sufficient accuracy and there is an extensive literature dedicated to this subject [2–4]. All these algorithms estimate the future load using a dynamical system model $L(t) = D(L(t-1), L(t-2), ...)$, whose parameters are estimated through the data ($\hat{D}(\cdot)$ is the estimate), and then predict the future value using previously measured values of the load as inputs,

$$\hat{L}(t) = \hat{D}(L(t-1), L(t-2), ...) \tag{1.1}$$

As the number of EVs increases, this approach may fail to predict the increasing volatile load effectively. Thus, our tenet in this paper is to treat the portion of the load due to EVs separately and make it visible by an information structure. The load can be written as

$$L(t) = L^N(t) + L^{EV}(t) \tag{1.2}$$

$L^{EV}(t)$ is assumed to be proportional by a factor $-g$ to the number of vehicles $N(t)$ actively charging at time t. We will still use traditional load forecasting techniques for the remaining part of the load, $L^N(t)$ and thus, all we need to have is a smart forecast of $N(t)$.

EVs will require charging access frequently as they are only able to travel around 100 miles on a full charge. Most of the customers travel back from work within a certain time window and it is predictable that they will plug their vehicles in for charging as soon as they reach home. Each EV will nearly need a power of 1.5 kW for charging and the duration of a full charge is about 6-8 hours. We call $C^{\max}$ the maximum charge time. A full charge is of course not always the case. It is foreseen [5] that the customers who will purchase EVs during the first decade of their appearance will mainly reside in certain neighborhoods and thus, if not controlled, this pattern will cause the transformer stations to overload and will nearly double the peak demand of the residential section.

The literature is considering two possible models to handle the EVs. One is emulating the gas station model, by replacing them with charging stations, which will essentially offer the service of managing sufficient reserve to provide the required charge. The question is what to do when the car is plugged directly to the grid. There are recent articles in the literature that discuss strategies to shift the load due to EV charging cycles to off-peak hours. Several of these papers rely on pricing strategies [6, 7]. Although this is a valid strategy, the reasonable concern is if these mechanisms will lead to stable network conditions, since they may offset a large chunk of the load simply moving the peak to a different time. Another issues with EVs is their mobility. How can one prevent energy theft if the activities of the EV are not carefully

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monitored? To avoid this, smart grid strategies envision an active management system that continuously monitors all the elements of the system and makes decision on when the EVs should start charging their batteries based on the amount of available energy.

Our paper is concerned with modeling the statistics of the load offered by EVs (in Sec. 2.1) and proposes an communication architecture (in Sec. 3) to accrue the data that would permit to enforce the correct actions. The work presented can be divided into two scenarios. In the first scenario, we have no control over the EVs but we have real-time data about their arrivals and the amount of energy required for a full charge by each of the vehicles. In this case, the new information is proven to be essential (c.f. Sec. 4) to reach accurate load forecast and thus, plan the generation accordingly. In the second scenario, we have an active control over the time at which each vehicle starts to charge its battery and we can use our authority to lower our peak generation cost. For both cases we outline a solution to manage the SmartGrid information that is based on associating charging events with a mobile cellphone application and service.

2. EV FORECASTING MODEL

EVs can be modeled as customers arriving in a queue to receive energy for charging (service). There are two options: (Scenario I) serving them immediately as they are plugged in, or (Scenario II) queueing them, controlling their access to energy. In both cases we quantize the charging duration of the EVs in Q levels, and denote by D_t the $P \times Q$ array containing the number of cars that arrived in interval t, in each charging class, based on charging duration (column) and price (row). We assume that $C^{\max}/Q = T$. Further, we call ε_t the $P \times Q$ array of cars unplugged before ending the required charge, in each charging duration and price class. We will assume that ε_t has negligible impact on $N(t)$. In Scenario II, we divide the customers in $P \times Q$-queues and update the array of queue-states S_t every t (see Fig. 1) and $a_t(i,j)$ is the number of *servers* allocated for each queue, which correspond to the number of cars in each queue that we start charging at time t, at price i and charging level j. In both cases, at each decision epoch, the control center receives via a communication infrastructure D_t. EVs arrivals can be modeled as a Poisson process with a time-dependent rate $\lambda(t)$. For simplicity, we assume that the charging times are independent and identically distributed and are also independent of the arrival process.

2.1. Scenario I: Uncontrolled Arrival Of Electric Vehicles

If no control is applied to the EVs access, charging starts at the moment when the EV is plugged in. The time t is discrete and the sampling interval is T. In this case, we can model $L^{EV}(t) = -gN(t)$ as the workload of an $M_t/GI/\infty$ queue, i.e. $a_i = \infty$ in Fig. 1. For this scenario we also consider a single price, i.e. $P = 1$ and all the arrays are vectors. Since no queue is even formed, $\forall t,\ S_t = 0$. Our goal is to predict the number of customers $N(t)$ that are receiving service from the system at a future time t. It was shown separately by Palm [8] and Khintchine [9] that when an $M_t/GI/\infty$ system is initialized at $t = -\infty$ with no cars (customers) in the queue, the number $N(t)$ of the cars present in the grid at time t will have a Poisson distribution with a mean that is a function of $\lambda(t)$ and the distribution of the charging time of the cars, $F_C(t)$. Define the random variable C_c with the associated stationary-excess or equilibrium-residual-life CDF[1] of

$$F_{C_c}(t) = \frac{1}{E[C]} \int_0^t (1 - F_C(v))dv, \ \ t \geq 0. \tag{2.1}$$

Then, the number of cars $N(t)$ charging from the grid at time t is a Poisson random variable with mean $m(t)$:

$$m(t) = E[N(t)] = E\left[\int_{t-C}^t \lambda(u)du\right] = E[\lambda(t - C_c)]E[C] \tag{2.2}$$

Since our system starts at $t = t_\circ$ with $N(t_\circ)$ customers, for which the remaining service times are known, then the number of cars present in the system at time t will be:

$$N(t) = N^{new}(t) + \nu(t) \tag{2.3}$$

where $N^{new}(t) = \sum_{q=1}^{Q} D_t(q)$ is a Poisson random variable with the mean given in 2.2, with $\lambda(t)$ set to zero for $t \leq t_\circ$, and $\nu(t)$, is deterministic and equal to $N(t_\circ)$ (the number of cars that where present at time $t_\circ$) minus those that departed before time t. Note that $\nu(t)$ is deterministic since, by knowing $D_k, \forall\ k < t$ we can derive $\nu(t) = \sum_{i=0}^{Q-1}\sum_{j=i+1}^{Q} D_{t-i}(j)$. Furthermore, $D_k, \forall\ k < t$ allows to estimate of $\lambda(t)$ and $F_C(u)$. The estimation of $\lambda(t)$ can be performed using the method described in [10]. $F_C(u)$ can be obtained from the average histogram of charging times, that can be also updated adaptively with a forgetting factor if necessary. In this Scenario I, while the EVs arrivals provide information to fill up the array D_t, there is no information feedback sent to the EVs, since their access is not controlled. The only feedback is physical, and consists in the energy dispatch

[1] This random variable frequently shows up in renewal theory.

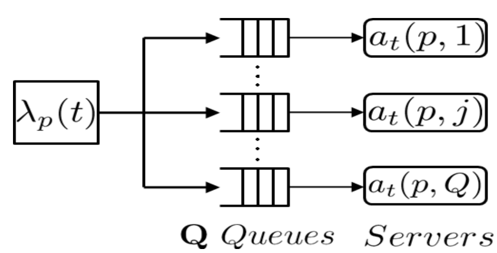

Fig. 1. Queuing model for price category p

that is adjusted according to the forecast. This is true unless the price is changed, and that has an effect on $\lambda(t)$: a useful remark is that if the price is updated at every interval t (dynamic pricing) $\lambda(t)$ will become considerably non-stationary and hard to track and models such as the one used in [10] will be insufficient to forecast the load statistics. Note that, since we serve any car that arrives, in principle we only care about the number of cars, not their charging classes. However, the subdivision in classes is needed to derive the statistics of $N^{new}(t)$ and to calculate $\nu(t)$.

2.2. Scenario II: Direct load management of EVs

In this scenario, the access to energy is controlled and, thus, the infinite server assumption is no longer valid. We consider two possible price classes: *green energy* and *traditional energy*. Hence, the customer is given the option to select electricity generated by wind, solar power or the traditional way. The arrival rates are $\lambda_i(t), i = 1, 2$ respectively. Green energy is cheaper but may have a longer waiting period.

The queues state matrix S_t follows the dynamics:

$$S_t = S_{t-1} - a_{t-1} + D_t - \varepsilon_t \tag{2.4}$$

where a_t is the $2 \times Q$ decision matrix with $a_t(i, j)$ = Number of vehicles in the ith supply method with charging duration j allowed to join the grid at time t. As mentioned, we will neglect the effect of ε_t. All the unfulfilled requests at each epoch are backlogged and no car is dropped from the queue. Thus, a part of the request at the next epoch is deterministic since it is equal to the current excess demand. The number of arrivals in the future interval in each supply category (i, j) is a Poisson random variable with mean

$$\alpha_t(i, j) = [F_C(c_j) - F_C(c_{j-1})] \int_{t-T}^{t} \lambda_i(t)dt \tag{2.5}$$

where $[c_{j-1}, c_j]$ is the charging interval that defines the jth queue. The model (2.4) is updated, by computing S_{t-1} based on the information received on the realized value for D_{t-1} and on the action performed a_{t-2}; with the model for the future $D_t(i, j)$ just discussed, the control center has the ability to forecast the statistics of S_t and plan the next action, which consists of: 1) updating if necessary the energy dispatch; 2) deciding a_{t-1}. In this case in addition to forwarding the information on D_t the control center has to feedback information that would allow to perform the control action a_t. To reach this goal, a message M_t with a dimension of $2 \times Q$ is broadcast, where the (i, j)th element of M_t consists of a time index $T_{i,j}$. The action is computed as follows: vehicles that are in the (i, j)th category, and whose arrival time is before $T_{i,j}$, can start charging right away; other vehicles have to wait until the next epoch. $T_{i,j}$ is computed from the equation

$$T_{i,j} = \max(\tau \le t : \sum_{k=\tau}^{t} D_k(i, j) \ge S_t(i, j) - a_t(i, j)). \tag{2.6}$$

3. COMMUNICATION INFRASTRUCTURE

One of the key aspects that is motivating the deployment of the Advance Metering Infrastructure (AMI) is accurate billing and remote disconnection. The deployment is not, however, really incorporating any basic ability to roam its customers and to track consumption of specific appliances in real time; hence, the surge of EVs will pose significant billing problems, in addition to the control problems discussed previously. Fortunately, the aggregate traffic of incoming vehicles may be mapped into modest information traffic. We identify two architectural functions are needed to manage EVs and outline possible sensible solutions to handle them: 1) mobility and roaming management; 2) sensing and data acquisition.

Mobility Management– Mobility management is a mature technology in wireless networks [11]. Rather than reinventing the wheel, we propose to integrate the management of EV mobility with the management of wireless device mobility. In fact, location based services to support the EVs can be a major area of expansion for the wireless market, generating relatively low traffic. Two international standards support (2G) mobility and they are both based on Signal System 7 (SS7) [11]: the Electronic/Telecommunications Industry Associations Interim Standard 41 (EIA/TIA IS-41) (AMPS and IS-54/IS-136 networks), and the GSM Mobile Application Part (MAP) (GSM, DCS-1800, and PCS-1900). Groups of geographically contiguous cells are managed by mobile switching centers (MSC) which update a database called visitor location register (VLR). Each subscriber is recorded in a higher level database called home location register (HLR) which is linked to the VLR of the area (including several cells) the subscriber is currently visiting. The updates on these databases occur when a terminal changes its base station which, upon detecting the presence of a new mobile, sends information to the MSC to update the VLR. If the Mobile Identification Number (MIN) is in the VLR nothing changes, otherwise the MIN is appended to the VLR and the MSC sends a message to update the HLR link, which authenticates the terminal with an ACK that also signals the successful update of the link registry. The previous VLR is also updated, removing the outdated entries.

Most cellphone technology is equipped with Bluetooth connectivity and, in necessary to corroborate the data, a GPS that allows to accurately time stamp and locate the mobile. It is only natural to associate the EV charge event to the same MIN number of the driver who is interested in charging the car. The billing can be bundled with other mobile communication services, as an EV billing plan, whose management cost can be spread among all the parties that benefit from this service.

When the vehicle is plugged, a smart plug will interact first with the cell user via Zigbee or Bluetooth to authorize the transaction, requiring a code or a password from the mobile user. Then, the smart plug will contact the Smart reader and communicate the MIN number and the charging parameters. If the Smart meter authorizes the charge to take place it will again contact the phone via Bluetooth and the phone will send a *charge activation* text message, to update an EV register (EVR) with the MIN, the location and the charging parameters for the transaction. When the vehicle is unplugged an *end charge* message, with the total battery charge accrued from the grid, is also sent to mobile phone, to acknowledge how much energy was absorbed, and to the Smart reader, which will subtract the consumption from the premise bill. The record of the transaction can be paged to update the EVR for the EV billing. Since the information of the EVRs is volatile it is natural to handle them in a way that is similar to VLR, and place them in the MSC.

Sensing and data acquisition- The same *charge activation* messages recorded in the EVR can be mined to construct the record of the realized D_t at a higher level, to update the forecasting and decide on the control actions. To do so, counters at each MSC can be maintained for each entry of $D_t(i,j)$ and information can be sent to the control center to aggregate the information and form D_t. In Scenario II a response mechanism tied to the SmartGrid infrastructure is required to broadcast the message M_t, thereby allowing the cars to activate their charge.

4. EXPERIMENT

We generated EV arrivals according to the $M_t/GI/\infty$ model we proposed and added that load to a normalized load curve from the database [12]. The arrival rate $\lambda(t)$ is a double-periodic rate with 24-hour and one week periods, generated using a $(1\times1\times0)\times(1\times1\times0)_{48}\times(1\times1\times0)_{336}$ ARIMA process [13]. we assumed that the charging time S (see Section 2.1) of each car will have a clipped Weibull distribution, truncated at 8 hours. The traditional method used models the load as an ARMA process [2]. To evaluate $m(t)$ in (2.2)., we forecasted the arrival rate of the cars using the same ARIMA model parameters used in generating the $\lambda(t)$ and then evaluated the integral (2.2) numerically. Fig. 2 shows the average normalized Mean Square Error of forecast of a set of load curves using the smart and the classical predictions. One can clearly observe that the classical technique prediction has an MSE that grows up to be an order of magnitude worse than the smart one, when the arrival rate climbs during night hours.

5. CONCLUSION

In this paper, we introduced a model to effectively model the arrival of EVs. We then showed that a direct load management of EVs does not necessarily need a direct link between every single EV and the control center and we proposed a communication structure to manage gathering and broadcasting the required data.

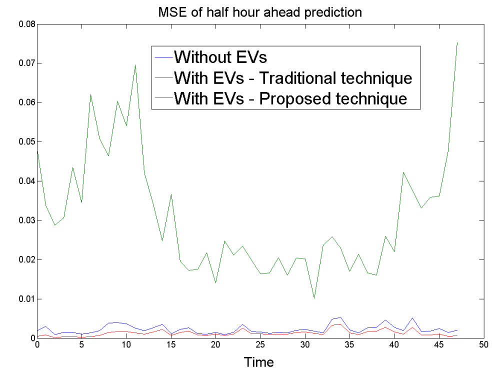

Fig. 2. Comparison of Normalized MSE of Predictions

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