Learning to Schedule Electric Vehicle Charging given Individual Customer Preferences

(Extended Abstract)

Konstantina Valogianni
Erasmus University Rotterdam
kvalogianni@rsm.nl

Wolfgang Ketter
Erasmus University Rotterdam
wketter@rsm.nl

John Collins
University of Minnesota
jcollins@cs.umn.edu

ABSTRACT

Electric Vehicles (EVs) and their integration in the smart grid are challenges that sustainable societies have to tackle. Large scale uncoordinated EV charging increases peak demand and creates the need for extra grid infrastructure to be covered effectively, which is a costly solution. We propose a decentralized charging strategy for EV customers that offers savings for the individual adopters on their electricity bill and at the same time peak demand reduction, alleviating smart grid from critical strains. We implement our charging strategy through learning agents that act on behalf of EV owners and examine the effect of our strategy under the prism of various market conditions.

Categories and Subject Descriptors

I.2.11 [**Distributed Artificial Intelligence**]: Intelligent Agents

Keywords

Electric Vehicles, Smart Charging, Trading Agents

1. INTRODUCTION

Electric Vehicles (EVs) are increasingly gaining popularity as means of individual commuting [3]. This vast adoption is attributed to the rising fuel prices that discourages the use of internal combustion engine vehicles (according to EU reports we had a quintupling of oil prices between 2002 and 2010 [5]). EVs make commuters independent from fuel prices, but increase their dependency on electricity prices and involves them in the *Smart Grid* energy exchange processes. EVs apart from transportation purposes may serve as Balancing Responsible Parties (BRPs) within Smart Grid. They can use part of their battery capacity for storing energy during low demand hours and feeding it back to the Grid during peak hours.

However, if they are not controlled properly, they can be disastrous for smart grid's stability, since EV charging creates high peaks on the demand, overloading the grid. To overcome this bottleneck we propose a distributed Smart Charging strategy implemented on the individual customer's side through a customer agent. This agent accounts for each individual customer's preferences and schedules EV charging maximizing the derived utility. We observe that by applying this strategy on the market the EV owners' comfort is not violated and the peaks in the demand are shifted towards lower demand periods. Meanwhile, the energy prices are reduced because of this peak shaving, yielding to savings for the individuals.

Appears in: *Alessio Lomuscio, Paul Scerri, Ana Bazzan, and Michael Huhns (eds.), Proceedings of the 13th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2014), May 5-9, 2014, Paris, France.*

2. MODEL DESCRIPTION

Each customer is represented by an agent that implements the EV charging strategy and calculates the charging vector based on demographic information, driving profiles and household consumption of the particular individual. Firstly, the agent determines the driving profile of each individual customer. It calculates the daily driving needs (driving profile) taking as inputs the gender, profession, working type and other demographic characteristics of the individuals.

Further, the customer agent defines the utility coming from energy consumption. Assuming that the total consumption consists of two components: household demand (KWh) and EV charging demand (KWh) we have the total utility derived by the total consumption. We assume quadratic utility forms as described in [1]. The quadratic form is just an approximation for the energy consumption utility and in the future we plan to collect real data to adjust this utility. The variable ω is an important component of our analysis and expresses the *level of satisfaction obtained by the user as a function of its energy consumption* and varies among customers. It can be interpreted as the customer's flexibility factor towards reaction to prices. The individual welfare is the total utility obtained by the consumption for a particular consumption unit reduced by the purchasing cost of this unit. We assume real time pricing, and as an example we use the European Energy Exchange (EEX) price-trends over 24h horizons.

Having calculated the driving pattern, the agent uses reinforcement learning [6] to learn customers' energy consumption pattern. The customer agents' decision problem is described by a Markov Decision Process (MDP) where each state represents the a discrete consumption value. The agent can only transition to states that refer to later time slots than the current time slot. After iterating over multiple states the agent calculates to a "learned consumption pattern" for each individual.

Taking as inputs the learned consumption and the individual driving characteristics, the agent schedules EV charging with respect to individual welfare maximization. For time horizon $N = 24h$ the agent calculates the charging vector from the individual welfare maximization problem. In other words, derives the charging vector that ensures maximum welfare for each point in this time horizon N. The maximization constraints are summarized to the agent's capability to charge from the grid the maximum power allowed by the customers' charging level. The lowest amount the agent can charge is zero.

3. EVALUATION

We evaluate the smart charging (SC) strategy in different populations and examine its effect on peak demand and price reduction, as a function of the EV ownership penetration. The simulation environment consists of diverse EV customer populations. The agent is trained on data provided by University of California Irvine (UCI) machine learning repository [2]. Basic assumption is that the EV customers buy energy from the market to cover both their household consumption and their EV charging demand.

First, we examine the effect of ω (*customer's flexibility factor*) on the individual demand. For higher ω values, the satisfaction the customer gets from consuming one particular amount of energy becomes higher. We implement 5 scenarios that cover extreme and average cases ($\omega = 0.9$, $\omega = 1$, $\omega = 10$, $\omega = 100$, $\omega = 1000$). We observe that the case of $\omega = 10$, $\omega = 100$, $\omega = 1000$ show exactly the same behavior because of the upper bound of the optimization. Therefore, from now on we will use $\omega = 10$ as the maximum value of ω for this experimental setting. We also implement one mixed scenario where all ω values are equally represented. We observe that higher value of ω, yields higher peak reduction, with a maximum reduction of 40%.

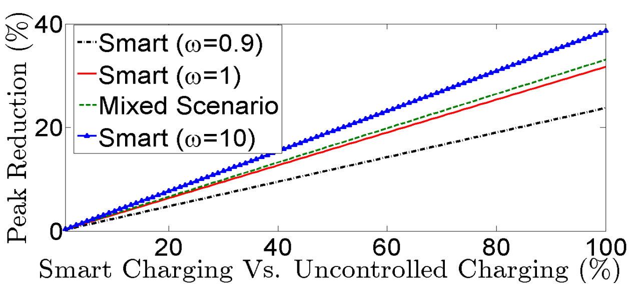

Figure 1: Peak Reduction.

Figure 2 displays the demand shifts because of Smart Charging for various ω. We observe that the highest ω value gives the highest shift. An immediate result of the previous figure is the price reduction. There is a general price reduction diffused in the market because of the demand shift and peak reduction. In Figure 3 we show this reduction for $\omega = 1$, $\omega = 10$ and for a mixed scenario with a maximum of 5% at 100% Smart Charging adoption, using EEX prices.

Finally, in Table 1 we show the peak reduction for various smart charging flexibility parametrizations (within the ω spectrum). We see that increasing customers' flexibility leads to increasing peak demand reduction, which is directly related to the demand shifts as a function of flexibility.

4. CONCLUSIONS & FUTURE WORK

We presented a decentralized charging strategy focusing on each individual EV owner. We showed that Smart Charging adoption leads to peak demand and price reduction on the market and savings for the individuals. This implies an emergent charging coordination based on preferences, without the presence of an actual coordinator. In our future work we plan to include the Vehicle-to-Grid discharging and extend the scheduling horizon to increase realism. Finally, we plan to integrate our strategy into Power TAC [4] for more thorough validation.

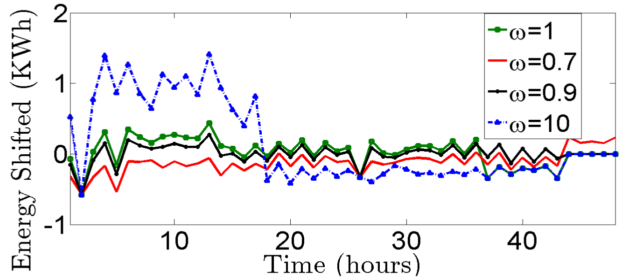

Figure 2: Demand Shifts over time for various ω.

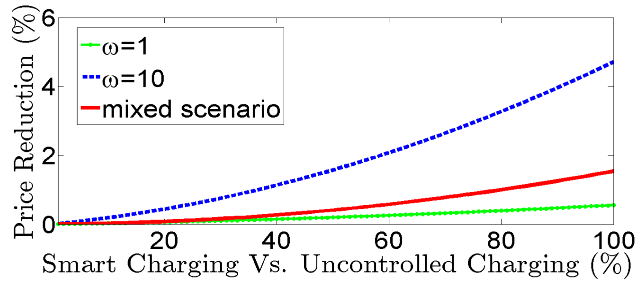

Figure 3: Average Price Reduction.

Table 1: Energy Peak Reduction

$(\omega = 0.7)$	$(\omega = 0.9)$	$(\omega = 1)$	$(\omega = 10))$
24%	33%	36%	39%

5. REFERENCES

[1] M. Fahrioglu and F. L. Alvarado. Designing incentive compatible contracts for effective demand management. *IEEE Transactions on Power Systems*, 15(4):1255–1260, 2000.

[2] A. Frank and A. Asuncion. UCI machine learning repository, 2010.

[3] International Energy Agency. *Global EV Outlook.* Organisation for Economic Co-operation and Development, Paris, 2013.

[4] W. Ketter, J. Collins, and P. Reddy. Power TAC: A competitive economic simulation of the smart grid. *Energy Economics*, 39:262–270, 2013.

[5] T. Maltby. European union energy policy integration: A case of european commission policy entrepreneurship and increasing supranationalism. *Energy Policy*, 55:435–444, 2013.

[6] R. S. Sutton and A. G. Barto. *Reinforcement Learning: An introduction*, volume 116. Cambridge Univ Press, 1998.