Available online at www.sciencedirect.com

SciVerse ScienceDirect

Procedia Computer Science 19 (2013) 847 – 853

Procedia
Computer Science

The 2nd International Workshop on Agent-Based Mobility, Traffic and Transportation Models, Methodologies and Applications (ABMTRANS'13)

Applying an Activity Based Model to Explore the Potential of Electrical Vehicles in the Smart Grid

Fjo De Ridder[a*], Reinhilde D'Hulst[a], Luk Knapen[b], Davy Janssens[b]

[a]*EnergyVille, Dennenstraat 7, 3600 Genk, Belgium, VITO, Boeretang 200, 2400 Mol, Belgium*
[b]*IMOB, Hasselt, Belgium*

Abstract

We have explored to what extent charging electrical vehicles (EVs) can be exploited to stabilize smart grids. Firstly, we discuss the transition to a future with a lot of renewable energy resources. Next, a decentralized coordinated charging schedule for EVs is proposed, taking into account the comfort settings of the consumers and local and temporal flexibility. Based on the vehicle behavior information (trajectories, parking places and duration, etc.) the algorithm assures that all vehicles can follow their planned trajectories and that power constraints on each car park are always met. An advantage of this decentralized coordination algorithm is that the privacy of consumers, including their future trajectory planning, charging controllers, parking duration, etc. are all treated on local processors on board. As a consequence the responsibility for constructing the charging schedules is put only with the vehicle owner. On the other hand, the parking managers need only to be concerned with the network congestion issues. A first application focuses on controlling the power flows at these parking locations and on rescheduling the charging of the electrical vehicles, so that costs are minimized within the comfort settings and within the physical limitations of the charging stations. This coordinated charging is applied on a car fleet of 200 electrical vehicles and 56 parking locations. Trajectories are computed with an activity based model (FEATHERS). In a second application, the imbalance costs are taken into account as well. The main advantage is for the retailer, who can now actively use the flexibility of the charging process to lower his power trading costs.

Selection and peer-review under responsibility of Elhadi M. Shakshuki

Keywords: Smart grids, Cooperative scheduling, Activity planning, Schedule generation, Electric mobility models, optimal and distributed control

1. Introduction

Wind turbines, combined heat and power installations, solar panels and other renewable energy resources are becoming more popular. The main drawback of this trend is that the power is no longer produced in a few large plants, which are easy to control. An additional problem is that the power production by these resources is often unreliable and unpredictable. This combined with the fact that

* Corresponding author. Tel.: +32 14 33 59 71; fax: +32 14 32 11 85. *E-mail address*: fjo.deridder@vito.be.

1877-0509
Selection and peer-review under responsibility of Elhadi M. Shakshuki
doi:10.1016/j.procs.2013.06.113

production and consumption must be in equilibrium at every instant can cause severe problems in the future grid. One solution to overcome this, is to make use of the flexibility of consumers: instead of tuning the production to the actual consumption, the consumption can follow the production. This is the paradigm shift used in many smart grid test cases. In the transition from the current situation to a smart grid, the comfort settings of most consumers cannot be altered. Heating, lighting, most industrial processes cannot be postponed if the production decreases. For that reason, charging electrical vehicles (EVs) offers an important opportunity to buffer variable production [1-6]. A second problem is that our distribution grid is not equipped to deal with large local peaks in production and consumption [7, 8]. Changing feeders and transformers is expensive. An alternative for these investments is to introduce variable tariffs, so that over-consumption can be avoided if the power grid cannot support this. In order to gain realistic results, three different concepts are combined. Firstly, information about the behavior of the EV owners, like: which trips are planned? When are the cars parked? How many cars are parked together? … are retrieved from an agent based model, FEATHERS [9]. The actual fuel consumption and battery capacity are based on today's state-of-the-art technology. Detailed information about the exact state of the distribution grid in Flanders is not available. For that reason, we did not take variations in the distribution grid into account and focused on only a few zones. The third component is the intelligence of the smart grid. A distributed controller is implemented to steer the charging schedules of the individual EV in order to minimize costs within the capacity constraints dictated by the power grid. In this study, a few possible business cases are explored. First we examine if it is above-all possible to charge all EVs with the current power grid. From these simulations it follows that if EVs are equipped with a coordination algorithm, the current grid capacity is sufficient. Next the battery systems are actively used to trade on the imbalance markets and thus to support the business model of a retailer.

2. Activity Based Models

To test the scheduling algorithm presented in paragraph 3, travel behavior information of the EVs is needed: the algorithm assumes that all EV owners have a day-ahead knowledge on what their travel behavior will be. This information is obtained using activity based modeling. Activity-based modeling (ActBM) is a technique that predicts the daily travel agenda (schedule) for each member of a synthetic population. Most ActBM generate predictions for a single day. For each predicted activity, the ActBM specifies the activity type, start time, duration, location as well as the duration and transportation mode for the trip to reach the activity location. Activity-based models are micro-simulators: behavior for each individual is simulated. This allows to investigate the overall effects of traffic demand management policies. FEATHERS is an operational activity based model for the region of Flanders (Belgium); it generates schedules for a given day-of-week.

FEATHERS input data consists of:

- the synthetic population for the study area. This contains socio-economic data (household composition, education level, income category, age category, etc.) describing each individual so that the distributions fit the census data.
- an area subdivision into traffic analysis zones (TAZ).
- land-use data for each TAZ. This consists of tens of attributes including number of people living in the TAZ for several age and employment categories, amount of people employed in the TAZ in several economic segments (industry, agriculture, education, distribution, hospitals, etc.).
- impedance matrices specifying the travel time and distance between TAZ for off-peak, morning-peak and evening-peak periods and for several transportation modes (i.e. car, slow, public transport).
- a set of decision trees trained using large scale (periodic) travel surveys. Those data essentially specify individual behavior as a function of socio-economic data and partial schedule characteristics. They are

used as conditional probability functions to sample agenda and activity attribute values for each individual.

The FEATHERS model is characterized by the data given in Table I. FEATHERS is built on the Albatross kernel described in [10]. It makes use of 26 decision trees to first predict the basic travel agenda containing mandatory periodic activities and related trips (work, school) and in a second stage the flexible activities (shopping, social visits, etc.). The decision trees are used in a fixed order that models the decision making process.. Each step determines new attributes for agenda components by stochastic sampling. The resulting schedules are consistent at the household level (resources available to the partners). The schedule (agenda) is constructed using several stages; this results in a chained decision process where each stage further completes the partially constructed agenda. The Albatross system is called a computational process model (as opposed to a utility maximization model). It is a rule-based system where the rules consist of decision tree based predictions. FEATHERS output consists of a travel schedule for each member of the synthetic population. For each predicted trip a tuple (origin, destination, start time, duration, mode) is predicted. This allows to calculate expected mode-specific traffic flows in time and space; those flows are validated using traffic counts made available by public traffic management services. FEATHERS predictions have been used in [11] to calculate the electric power demand generated by EV charging for each TAZ in Flanders as a function of time under several charging behavior, EV market share and charging opportunity (at home, at work) assumptions. The simulations to test the EV charging algorithm proposed, use FEATHERS predicted schedules as input data. Both the locations where EV induced electric power demand occurs and the corresponding charging time intervals are taken from FEATHERS results. Note that the distance between charging opportunities available to the individual are important. Only a small selection of EVs is used for two reasons: (i) hardly any details about the power distribution grid in Flanders are available. Since the grid would look uniform all over Flanders, large scale simulation would not reveal more information than small ones. Secondly, the control algorithms are designed to be distributed over multiple computers, but all computations are still performed on a single machine. This practical reason limits the number of participants also to a few hundred at most. We selected those EVs which are parked at ten locations. Grid constraints are downscaled to mimic the consumption of other EVs and of background consumption.

Table 1. Characteristics of the input data for Flemish activity based models.

Synthetic population size	6 million people
Number of TAZ	2368
TAZ area (average value)	Approx. 5 km^2
Number of diaries in survey	Approx. 8000

3. Simulation Results

To illustrate the algorithm, a simulation was carried out where charging schedules were constructed for 200 EVs. From the FEATHERS predicted travel schedules for the EVs, there are 56 locations where at least one vehicle is parked during the day. The electricity tariff for all EVs is assumed to be equal, and is an hourly varying dynamic tariff. This dynamic tariff is based on the day-ahead tariffs of the Belgian Power Exchange (Belpex) [12]. The maximum charging power of the vehicles is set to 3.6 kW. The maximum power available for charging EVs at every location is set to 14.4 kW, so only 4 EVs can charge at full power simultaneously at every location. Every vehicle is assumed to have a battery capacity of 24 kWh [13]. The state of charge of the EV batteries at the beginning of the day is assumed to lie between 90% and 100%. When cars are driving, they consume a 200Wh/km [14], and we assume an average driving velocity of 50 km/h. The simulations are carried out for one day, with a time-step of 5 minutes. A simulated day starts at 3 am. The distributed control scheme consists of an individual utility function for each EV consisting of the price for charging and a small quadratic term, taking power losses into account. Each utility function is subject to a set of constraints. Global constraints, like the limited charging capacity of the car parks and the overall imbalance power are passed to these utility functions by means of Lagrange multipliers [15-16]. The value of these Lagrange multipliers is adapted iteratively until all global constraints are met. The main disadvantage of this method is that solutions have to be iterated, which causes a larger communication overhead between the local EV solvers.

As a benchmark, the solution to the global minimization problem is calculated using linear programming. In this centralized optimal solution, the overall cost that needs to be paid to charge all EVs is 37.9 euro. After about 100 iterations, convergence is reached: the electricity cost paid by all EV owners reaches the benchmark value, and the maximal charging power encountered at the parking locations does not exceed its maximum value. However, already after about 30 iterations the electricity cost paid by the EV owners differs less than 0.1% from the optimal value, and the maximal power encountered at the charging locations is less than 10% higher than its maximum. Fig. 1 shows the total charging power at every location versus the time of day, calculated after the first iteration, and after convergence is reached. A darker color indicates a higher power. Red colors indicate that the capacity limit is reached. The figure clearly shows that the algorithm forces the EVs to charge at other locations when the maximal power constraint is violated.

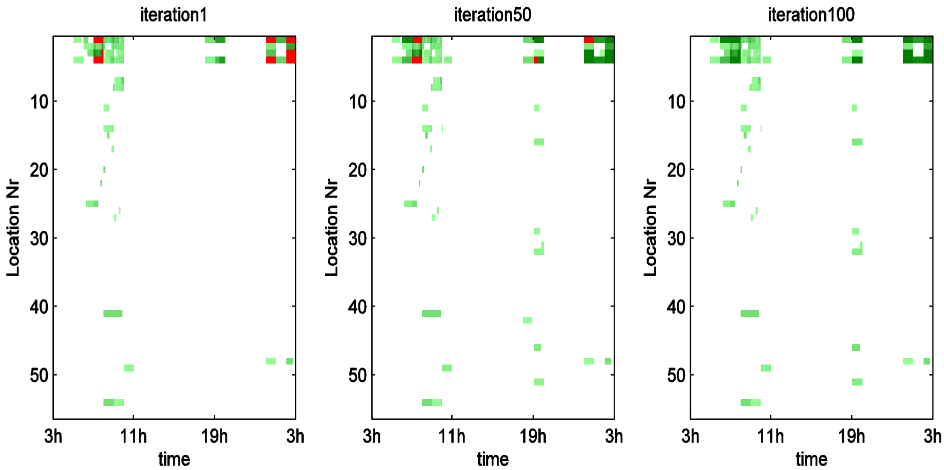

Fig. 1. Total charging power at each location versus time of day at the 1st and the final iteration. A darker color indicates a higher charging power.

In a second application, the charging flexibility of the EV is used to lower imbalance costs for the retailer. Retailers have to predict the consumption 24h in advance and buy this power on a day-ahead market (DAM). Deviations from this predictions have to be traded in real time on the imbalance market. Prices fluctuate more rapidly on the imbalance market and prices for a positive or negative imbalance differ. Since the exact charging moments are usually not critical for EV, this creates an opportunity to charge at strategic moments: it will be beneficial to charge when (i) the predictions overestimated the actual consumption and a positive imbalance is created; or when (ii) the negative imbalance prices are lower than the day-ahead prices and the charging prices are thus lower on the imbalance market than on the day-ahead market. On the other hand, it is beneficial to post-pone charging when (i) predictions underestimated the actual consumption and the overall portfolio of the retailer is thus already negative; or when (ii) the prices for a positive imbalance are larger than the DAM prices. In the latter case cheap power bought on the DAM is sold more expensively on the imbalance market. If this imbalance market is

incorporated in the simulation, it appears that the optimal charging does not result in minimized overall imbalance power, but rather strategically causes imbalances. When charging now on the imbalance market is cheaper than on the DAM, EVs charge more than planned. This results in additional flexibility, which is used later to lower imbalance costs when these exceed the DAM price.
Simulations are run over 48h for three cases: a benchmark case, where every EV charges as fast as possible. Here no strategy is taken into account. Next, EVs can only chose when to charge and finally EVs can both charge and discharge. Fig. 2 summarizes the results. We split the power imbalance in two groups, depending on the ratio between the imbalance price and the DAM price. In the left column, imbalance prices are below DAM prices and it is thus beneficial to charge more than originally scheduled. In the right column a positive imbalance is most beneficial, since the redundant energy can be sold above the DAM price. The benchmark case is insensitive to this ratio, which results in an average imbalance cost of 121 €/EV/year. If EVs can only charge, the left distribution can be altered. This change in behavior results in a reduction of the imbalance costs with 60 % to 46 €/EV/y. If EVs can both charge and discharge, they can also benefit from high prices on the imbalance market, which can be seen in the outliers on the right graph. The left graph remains almost unchanged. Overall the retailer can gain on the imbalance market and made a profit of about 128 €/EV/year.

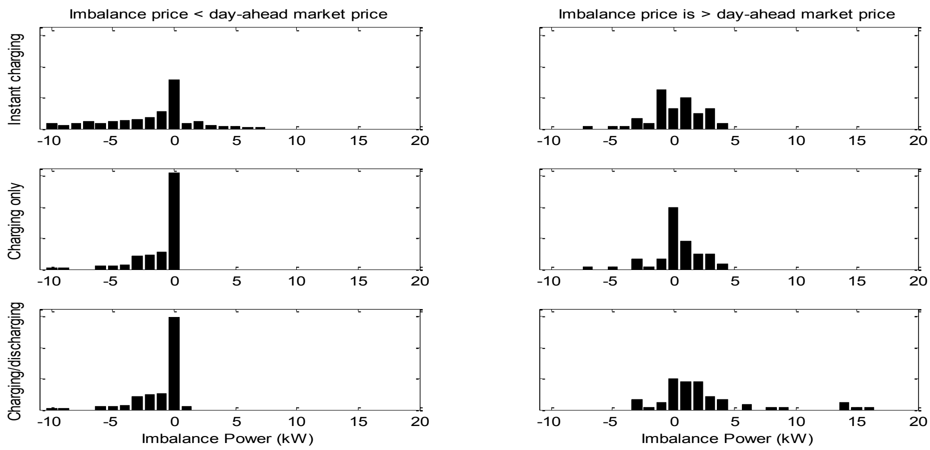

Fig. 2. Total charging power at each location versus time of day at the 1st and the final iteration. A darker color indicates a higher charging power.

4. Conclusion

An algorithm is proposed for constructing EV charging schedules, taking into account a maximum charging power constraint at each charging location and the individual energy consumption of each EV. The charging schedules are constructed day-ahead, given a (time-varying) electricity price, and given a known trip schedule for the following day. The algorithm is a price-based demand response algorithm, and is based on a dual decomposition technique. A first advantage of the proposed approach is that geographical information is included in the coordination method, and constraints of charging at different locations are taken into account. Vehicle owners are given an incentive to charge at other locations when power constraints at the charging location are violated. A second advantage is that the calculations are performed in a distributed way, to put the responsibility for constructing charging schedules only at the EV side. This contrasts with approaches where all, possibly privacy sensitive, information to form vehicle schedules needs to be gathered in one central location. Thirdly, convergence of the proposed algorithm is guaranteed for not-strictly convex utility functions for the EVs. The functioning of the algorithm is illustrated in two applications. Evidently, nowadays the number of EVs is too small for these problems to occur and the practical implementation of this coordination algorithm falls beyond the scope of this research.

Acknowledgements

The research leading to these results has received funding from the European Union Seventh Framework Programme (FP7/2007-2013) under grant agreement nr. 270833.

Appendix

For every EV an individual optimization problem can be formulated

$$[p_i(t), q_i(t)]^* = \arg\min \sum_t^T \left[\left(p_i(t) \left(\lambda^{\text{DAM}}(t) + \mu_{\text{imb}}(t) + \mu_{\text{capacity}}(t) \right) + \varepsilon_i p_i^2(t) \right) T_S \right] - q_i(T) \lambda_{\text{mean}}^{\text{DAM}}$$

subject to

$$\begin{aligned} \mathrm{q_i}(t+1) - q_i(t) &= \mathrm{c_i}(t) + p_i(t)\delta_i(t) && \forall t, \forall i \\ q_i(1) &= q_i^{\text{initial}} && \forall i \\ 0 \le q_i(t) &\le \overline{q}_i && \forall t, \forall i \\ \underline{p}_i \le p_i(t) &\le \overline{p}_i && \forall t, \forall i \end{aligned}$$

with indices $t = \{1, \ldots, T\}$ Index used to number discrete time intervals and $i = \{1, \ldots, N\}$ index used to number EVs; environmental parameters: $\mathrm{c_i}(t)$ consumption of EV, $SLP(t)$ estimation of background consumption and EV consumption, $\delta_i(t)$ is a parameter which is zero if EV is consuming and one if EV is parked, λ^{DAM}, $\lambda_{\text{mean}}^{\text{DAM}}$ are energy price on the day-ahead market (subscript 'mean' is the mean energy price over the horizon); control parameters $p_i(t)$ is the power consumption of EV, $q_i(t)$ is the battery capacity of EV, $\mu_{\text{imb}}(t)$ is the Lagrange multiplier concerning the imbalance and $\mu_{\text{capacity}}(t)$ the Lagrange multiplier concerning the grid capacity; and parameters q_i^{initial} is the initial battery capacity, T_S the time interval period, ε_i energy losses due to (dis)charging EV, $\underline{p}_i$ lower bound for (dis)charging the EV (0 if no vehicle to grid technology is present; $\overline{p}_i$ otherwise, $\overline{p}_i$ upper bound for loading EV, $\overline{q}_i$ upper bound for EV capacity. Power has the dimension [kW], energy [kWh] and prices [€/kWh], time in in [h]. This problem can be solved locally in every EV. So most information is used only locally.

The retailer's optimization problem is given by

$$\left[\Delta^+(t), \Delta^-(t)\right]^* = \arg\min \sum_t^T \left(\lambda^{\text{DAM}}(t) - \lambda^+(t) - \mu_{\text{imb}}(t) \right) \Delta^+(t) T_S - \left(\lambda^-(t) - \mu_{\text{imb}}(t) \right) \Delta^+(t) + \varepsilon \left(\Delta^+(t) - \Delta^+(t) + SLP(t) \right)^2 T_S$$

subject to

$$\begin{aligned} 0 \le \Delta^+(t) &\le \overline{p} && \forall t \\ -\overline{p} \le \Delta^-(t) &\le 0 && \forall t \end{aligned}$$

With $\lambda^{+}(t)$ the energy price for left-over energy on the imbalance market, $\lambda^{-}(t)$ the energy price for energy shortage on the imbalance market, $\Delta^{+}(t)$ the left-over power of the aggregator, $\Delta^{-}(t)$ the power shortage of the aggregator, ε are energy losses due to transport, $\overline{p}$ Upper bound for power transport
This equation can be solved autonomously. This set of optimization problems has common Lagrange multiplicators $\mu_{\text{imb}}(t)$ and $\mu_{\text{capacity}}(t)$. Both can be estimated with a relaxation method. This type of coordination mechanisms work well as long as all actors cooperate. So implicitly, we assume that cheating is not allowed. This principle is widespread and is in use in many energy market, like the Belgian day-ahead market.

References

[1] International Energy Agency (IEA), *Technology Roadmap*, Electric and plug-in hybrid electric vehicles, 2011.

[2] Pieltain L, Fernandez T, San Roman G, Cossent R, Domingo C, Frias P, "Assessment of the impact of plug-in electric vehicles on distribution networks," *IEEE Trans. Power Syst.,*2011;**26(**1):206–213.

[3] Dyke K, Schofield N, Barnes M, "The impact of transport electrification on electrical networks," *IEEE Trans. Ind. Electron.,*2010;**57**(12):3917 –3926.

[4] Ghijsen M, D'hulst R, "Market-based coordinated charging of electric vehicles on the low-voltage distribution grid," in Smart Grid Modeling and Simulation (SGMS), *2011 IEEE First International Workshop on*, 2011: 1 –6.

[5] Lopes JAP, Soares FJ, Almeida PMR, "Integration of electric vehicles in the electric power system," *Proc. IEEE,* 2011;**99**(1):168 –183.

[6] Shao S, Pipattanasomporn M, Rahman S, "Grid integration of electric vehicles and demand response with customer choice," *IEEE Transactions on Smart Grid,* 2012;**3**(1):543 –550.

[7] Clement-Nyns K, Haesen E, Driesen J, "The impact of charging plug-in hybrid electric vehicles on a residential distribution grid," *IEEE Trans. Power Syst.,* 2010;**25(**1):371 –380.

[8] Sundstrom O, Binding C, "Flexible charging optimization for electric vehicles considering distribution grid constraints," *IEEE Transactions on Smart Grid,* 2012;**3(**1):26 –37.

[9] Knapen L, Kochan B, Bellemans T, Janssens D, Wets G, "Activity based models for countrywide electric vehicle power demand calculation," in Smart Grid Modeling and Simulation (SGMS), *2011 IEEE First International Workshop on*, 2011: 13 –18.

[10] Arentze TA, Timmermans HJ, "A learning-based transportation oriented simulation system," Transportation Research Part B: Methodological, 2004;**38**(7):613 – 633.

[11] Knapen L, Kochan B, Bellemans T, Janssens D, Wets G, "Using Activity-Based modeling to predict spatial and temporal electrical vehicle power demand in flanders," *Transportation Research Record*, 2012.

[12] "Belgian power exchange." [Online]. Available: www.belpex.be

[13] Weller H, "Smart battery management systems," in *Joint EC /EPoSS / ERTRAC Expert Workshop 2010*, November 2010. [Online]. Available: http://www.green-cars-initiative.eu/workshops/joint-ec-epossertrac-expert-workshop-2010-on-batteries

[14] Tuffner F, Kintner-Meyer M, "Using electric vehicles to mitigate imbalance requirements associated with an increased penetration of wind generation," in *Power and Energy Society General Meeting,* 2011: 1 –8.

[15] Boyd S, Vandenberghe L, Convex Optimization. *Cambridge University Press*, 2004.

[16] Larsson T, Liu Z, "A lagrangean relaxation scheme for structured linear programs with application to multicommodity network flows," *Optimization: A Journal of Mathematical Programming and Operations Research*, 1997;**40**:247–284.