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DOI
10.1109/SmartGridComm.2017.8340707

Publication date
2017

Document Version
Accepted author manuscript

Published in
Proceedings 2017 IEEE International Conference on Smart Grid Communications (SmartGridComm 2017)

Citation (APA)
Hijgenaar, S., Erkin, Z., Keviczky, T., Siemons, J., Bisschops, R., & Verbraeck, A. (2017). A decentralised energy trading architecture for future smart grid load balancing. In *Proceedings 2017 IEEE International Conference on Smart Grid Communications (SmartGridComm 2017)* (pp. 77-82). IEEE. https://doi.org/10.1109/SmartGridComm.2017.8340707

A Decentralised Energy Trading Architecture for Future Smart Grid Load Balancing

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***Abstract*—Current state-of-the-art electric vehicle charging is found to have a profoundly disruptive effect on decentralised grids, increasing prevailing peak demand and causing network congestion. However, when charging behaviour is aligned with the needs of the grid, the batteries of electric vehicles can be used as a distributed resource to provide ancillary services. This paper proposes an decentralised algorithm that is capable of exposing the benefits of an electric vehicle fleet to grid system operators, taking the user preferences of the individual owners into account and keeping the application lightweight through a decentralised architecture. The algorithm is implemented in an agent-based model based on real Dutch smart metering data. The architecture is shown to decrease local imbalances, offer financial incentives to electric vehicle owners and maintain a minimum state-of-charge at departure for individual system users.**

I. Introduction

Electricity systems in the 21st century are in sharp transition. This energy transition is fuelled by the increased anxiety about our planet's sustainability. Mankind's concern with the environment has lead to the accelerated adoption of technologies that try to mitigate the exhaust of harmful gases to the Earth's atmosphere. The widespread introduction of plug-in electric vehicles (PEVs), both hybrid (PHEV) and fully electric (BEV), is an example of those technologies, as efforts to reduce harmful human impact can benefit from electrifying the transportation sector, one of the most polluting sectors.

However, by introducing large numbers of PEVs into our electricity systems, uncertainty in power management is increased. Charging behaviour can have profound effects on the quality of electricity supply, potentially doubling a household's need for energy [1]. The peak demands that result from the plug-and-charge standard, still the primary charging mode, coincides to a large extent with prevailing household peak demand. As a result, grids suffer from increased occurrences of congestion and frequency fluctuations [2].

PEVs are not the only distributed resources that have seen increased usage over the last decades. Technological advancements and incentive schemes by governments have led to attractive investment circumstances for decentralised renewable energy generation (REG), such as rooftop solar panels, small wind turbines and heat pumps. While these resources offer a more sustainable outlook for the future of electricity consumption, their integration in existing grids can further increase system operation complexity. Consumers become prosumers and expect reversal of flow for any overproduction from their own generators.

Often, modern energy systems are based on the principles of transactive energy, i.e. using market mechanisms to manage generation and load. Market parties, such as transmission system operators (TSOs), are tasked with keeping grids in balance by buying ancillary services. "Ancillary services are those services provided by generation, transmission and control equipment which are necessary to support the transmission of electric power from producer to purchaser. These services are required to ensure that the system operator meets its responsibilities in relation to the safe, secure and reliable operation of the interconnected power system" [3]. As a consequence of the energy transition, problems arise at a decentralised scale, while our systems try to solve them centrally. With the trends of the energy transition expected to propagate further, centralised control will become infeasible in the future.

In this work, we propose a decentralised energy trading architecture that can exchange the capacity of distributed resources amongst energy peers. By interconnecting prosumers and consumers in decentralised smart grids, the control of ancillary services can be decentralised, leading to a more efficient and transparent transactive framework. The algorithm incorporates both individual user preferences and system objectives, while maintaining system security and grid quality.

In order to validate our ideas, we designed an agent-based model to simulate patterns of generation and consumption based on Dutch smart metering data, collected from two hundred households in the city of Zwolle. The data set consists of power consumption of households in 15 minute intervals including solar energy generation pattern. Electric vehicle agents, for home-work-home trips and at public charging stations, are stochastically attributed energy demands. We tested the model using the local energy trading algorithm for its ability to minimise imbalance and minimise strain on individual users. The algorithm incorporates both smart charging and discharging.

To the best of our knowledge, our work is the first study that investigates a combination of smart charging and discharging in smart grid environments, providing a realistic model for local energy trade based on a decentralised architecture. As a result of the algorithm's distributed character, we are capable of combining both system requirements and individual user preferences, while maintaining computational feasibility. The results clearly indicate that the proposed solution lowers local imbalances, maintains a minimum state-of-charge for system users and offers financial incentives to electric vehicle owners.

II. Related work

Demand responsive charging, or smart charging, is an aggregated control scheme to limit excessive load by PEVs at times of high network load. [4] models users' readiness to change loading profiles by introducing a willingness to pay (WtP) parameter. The WtP adheres to the flexibility that PEV owners have considering their travel plans and state of charge (SOC). In the model user agents adapt their WtP according to their preferences, resulting in a certain charging speed - higher WtPs result in higher charging speeds. In [5] a charging algorithm is constructed based on the usage constraints of the users. The algorithm builds on [6] and features an aggregated optimisation of the energy price over the day. Through simulation the algorithm is proven to achieve valley-filling, shifting the PEV demand peak from the evening to during the night. [7] developed a charging algorithm that includes the battery degradation cost. The authors show that a system-optimal strategy can be found if PEV users make a trade-off between their own charging costs and local generation costs. In [8] a method is introduced where aggregators decide on revenue-optimising energy prices. PEVs then decide on their charging profile based on their specific charging requirements. The proposed algorithm does not incorporate load problems, but does show that social optimum can be achieved through the use of PEV aggregators. According to [9] pricing algorithms can account for the intermittent character of some renewable energy sources (RESs), causing prices to rise in time of shortfall and thus low PEV load. Waraich et al. show in [10] that dual tariff pricing mechanisms, e.g. night time discounts, might cause behavioural adaptation, but is likely to damage the grid further. The authors conclude that communication between vehicles and grid is required so that smarter charging schemes can be introduced. Based on quadratic programming [11] proposes an algorithm that can minimise power losses and voltage fluctuations while decreasing peak power. They acknowledge the associated costs with coordinated charging. [12] states that smart charging solely targeting valley-filling causes PEV owners to align their charging during the night, resulting in additional peak loads. [13] uses load predictions to calculate desirable charging speeds and durations. The goals are to minimise overall peak load and to balance the load profile. The authors show that the algorithm leads to desirable effects, while only requiring household electricity consumption data.

According to [14] storage capacity can effectively lower the operational cost of distributed power systems. There are many forms of storage capacity, but especially battery technology seems very promising, as a result of recent technological advances. These advances will accelerate the adoption of distributed generation (DG) from RESs, possibly leading to an increase in the value of renewable energy [15]. As the value of renewable energy goes up and owners have reasonable certainty that value is persistent, DG is incentivised. PEVs are considered to be one of the primary sources for storage [16], [17]. [12] shows that PEVs are unused for most of the day. The power invested in the automotive fleet is enormous [18], thus even when only a small proportion of parked vehicles can be connected to the grid, they can increase the quality of power supply, lower system costs and provide mitigation for the intermittence of renewable energy generation (REGs) [19], [20].

III. Background

As a result of European Union legislation, several European countries liberalised their electricity and gas markets. This has lead to competitive sectors being introduced to markets where aggregated curves for supply and demand result in market energy prices. Demand is estimated by balance responsible parties (BRPs) based on assumptions and generalisations. As a result, mismatches occur between estimated and actual consumption, causing local imbalances.

Local imbalances are increased as a result of environmental concerns, driving society towards sustainable technologies. Such technologies include distributed REG, commonly known as distributed resources (DRs). The output of DRs are often hard to predict over an aggregated control area, leading to bigger estimation errors and thus increasing local imbalance. With the widespread adoption of sustainable technologies consumers become prosumers and create dynamic local oversupply/overestimation. PEVs can be seen as another type of DRs that can create local undersupply/underestimation, through their unpredictable charging behaviour. With the most commonly used charging mode being plug-and-charge, charging behaviour often increases prevailing peak load conditions.

To balance grids, TSOs are dependent on ancillary service providers. These electricity producers have quick ramping generators that can give a balancing supply on short notice. Ancillary service providers are paid a fixed fee per time unit of availability and extra for when their service is called upon. The most interesting of ancillary services for this case is primary frequency control: the real-time matching of local load and supply. These services often require small amounts of energy for brief periods of time, however with the shortest response times, making it an ideal target service for PEVs as DRs.

IV. Our proposal for decentralised energy trade

We present an agent-based model (ABM) that can analyse the effects of PEV charging behaviour when introduced in a smart microgrid environment. Modelling agents that can interact with the environment following a set of elementary rules, can help in understanding emergent behaviour in various social contexts [21]. By using agent technology, simple car battery models, grid conditions and social trends can be used

TABLE I: Parameter values for the base, short term and long term future scenario

Parameter	Base scenario	Short term	Long term
Car owners fraction	0.72	0.72	0.72
PEV owners fraction	0.01	0.25	0.80
REG owners fraction	0.06	0.17	0.57
BEV fraction	0.01	0.80	0.90
Public charging stations	5	15	50
Average occupancy	0.134	0.134	0.134
Number of households	107	107	107

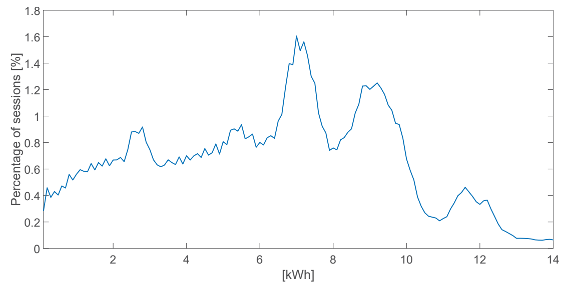

Fig. 1: Probability distribution of charging amounts in The Netherlands [22].

to examine the applicability of a PEV fleet as grid support. This will be tested in the current, a short term future and a long term future scenario.

A. Data

The base of the ABM is formed by a Dutch neighbourhood. The ABM features 107 agents simulating households. The input database was taken from the central energy management system (CEMS), a tool developed by CGI Nederland B.V. to balance decentralised grids. The database contained data of a pilot project (name omitted due to confidentially), where quarter-hourly smart metering data was collected of household energy consumption and generation. The simulation span covers a week, from 5-9-2016 through 11-9-2016. The database's historic consumption patterns are compared to the expected consumption patterns based on electricity load profiles of 2016. Electricity profiles define, for each 15-minute interval, a fraction of the yearly estimated consumption (YEC). Thus, each household's 2015 consumption is summed up. The profile category *E1B* was used because the participating households had different tariffs for day and night consumption. The dataset also featured generation data from rooftop solar panels, which was also added to the model.

B. Input parameters and scenarios

To simulate accurate representations of the system in its current and future states, input parameters and their progression through scenarios was based on Dutch policies and governmental plans. Moreover, technological advancements, such as the introduction of the Tesla Model 3 and battery technology improvements, were also taken into account. The parameters are given in Table I.

C. Agents

AnyLogic [23] was chosen as software tool, as it offers a direct connection with MSSQL server instances, offering a direct link with the dataset. The model contained four types of agents as sub-agents of the model's Main agent. What follows is a brief explanation of the four agents and their relationships.

a) Household: agents form the backbone of the smart grid model. Households are generated based on the input data stored in the CEMS database, thus owning an Id and YEC. Based on the Id, energy patterns are queried from the database for every 15 minute interval, i.e. period, of the simulation time span. The YEC was used to calculate estimated consumption patterns, that were stored with the amount of consumed and generated electricity data in watt-hours. In the base situation 107 agents are modelled, but this number can be decreased by removing households from the back of the list, or increased by duplicating database entries. Household agents can own a PEV agent, stochastically assigned by drawing from a Bernoulli experiment, using the PEV owners fraction as success rate. Another Bernoulli experiment, based on the REG owners fraction, is used to model the appropriate REG penetration. If a household does not have REG, its patterns of generated electricity are not included in the aggregated curves or trading algorithms.

b) Charging station: agents simulate the public charging infrastructure in the grid. Charging stations have a statechart with two states: unoccupied and occupied. Each agent is created in the unoccupied state and gets a power output by drawing from a uniform distribution of 3.7, 7.4, 11 or 22 kW. These outlet powers were based on Dutch infrastructure, excluding fast chargers [24]. Charging stations can transition from the unoccupied to the occupied state when a PEV agent arrives. PEVs arrive at charging stations following an expression based on the average occupancy. When a connected PEV's sojourn time has passed it is removed and the charging station agent transitions back to the unoccupied state.

c) PEV: agents can either be owned by a household or connected to a charging station agent. PEVs are either fully, or hybrid electric, assigned through Bernoulli draw based on the BEV fraction. PEV models are assigned according to Dutch penetration [25]. Charging behaviour is modelled stochastically (see Figure 1) and sojourn times are taken from [26] for publicly charging vehicles or based on normal distributions.

d) The aggregator: agent executes the trading algorithm. It takes all households and connected PEVs into account and spreads charging or discharging allocation equally, following a set of logical operators.

D. Algorithm

The core of the model is formed by the trading algorithm that enables local exchange of energy between EVs and households. At every time step t, the grid's conditions are analysed by looking at the actual and estimated consumption and the generation of each household $i \in I$, respectively $E^a_{i,t}$, $E^e_{i,t}$ and $E^g_{i,t}$:

$$\sum_{i=0}^{T} \left[E^e_{i,t} - E^a_{i,t} + \max\left(0, E^g_{i,t} - E^a_{i,t}\right) \right]. \quad (1)$$

The algorithm checks whether the grid is in under- ((1) <0) or overestimation (v.v.) and if household agents are either supplier or consumer of additional energy. In case of underestimation, at each t, for every PEV that has an active grid connection $j \in J^a$ it is tested if a full battery is achievable considering its remaining sojourn time $t^{soj}_{j,t}$, its $SOC_{j,t}$, max capacity C^{max}_j and outlet capacity P_j. If so, the PEV is added to the discharging set J^d:

$$\{j \in J^d \mid j \in J^a \text{ and } (1 - SOC_{j,t}) * C^{max}_j < P_j * t^{soj}_{j,t}\}. \quad (2)$$

The available energy for grid compensation is then:

$$\sum_{j=0}^{J^d} \min(P_j * t_{step}, (SOC_{j,t} - SOC_{j,min}) * C^{max}_j), \quad (3)$$

where $SOC_{j,min}$ is the minimal desired SOC of the respective owner. The result of (3) is then allocated equally amongst the consuming households. In case over overestimation, a similar calculation is done based on the available energy from REG and the charging requirements of J^a.

E. Criteria

There is a clear distinction between performance on a system level and on the individual user level. From a system's perspective the main purpose of local trading is to match estimated and actual demand, thus avoiding local imbalances and the need for expensive intra-day market trading. This is measured using the deviance between estimation pattern and emerging total consumption. The algorithm requires input from its users. Thus, an important barrier for the technology's success is the willingness of users to adopt the system and adapt their energy consumption routines. Based on these considerations, charging sessions costs will be used as a means to test performance from a user's perspective. It is likely that during times of underestimation the system would benefit from discharging PEVs, which introduces the risk of empty batteries. If this would be the case at PEV departure, users might become reluctant to partake in local trading. Therefore, the performance from a user's perspective will also be measured using the SOC at PEV departure.

V. Simulation Results

Figure 2 shows a single run of the base scenario. It is evident from the shaded area in the figure that, in this specific run, PEV demand increases imbalance during periods of underestimation and has the potential to change situations of overestimation into conditions of underestimation. To test the influence of stochastic variables in the model on simulation behaviour Monte Carlo experiments were conducted with 30 runs using unique simulation seeds. Over all runs, for each

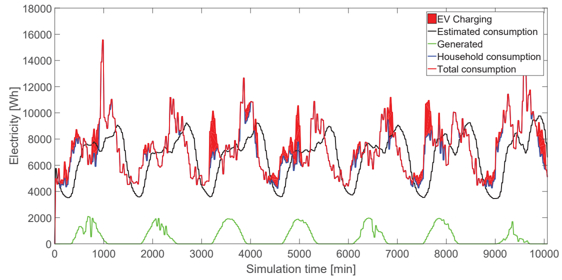

Fig. 2: Output of a single run of the ABM in the base scenario (6% REG penetration, 1% PEVs).

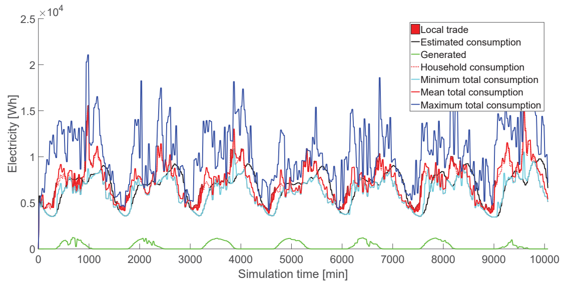

Fig. 3: Simulation results of the Monte Carlo experiment in the base scenario with local trade.

15 minute interval, the minimum, mean and maximum total consumption is collected (see Figure 3).

When the local trading algorithm is activated (Figure 3), it is shown that using local energy trading can help in balancing decentralised grids. When the minimum consumption equals the estimated consumption the algorithm is able to perfectly match the grid's consumption to what was expected by a BRP, thus ruling out the need for intra-day trading. Moreover, by looking at the mean total consumption one can see that by local energy trading, shown by the shaded red areas, the grid's consumption more closely matches the BRP's estimation than the household consumption. However, the effects are only minor.

By looking at the results of the Monte Carlo experiments for the short and long term future, we can conclude the aforementioned positive effect increases with growing numbers of PEVs and increasing shares of REG. For each of the three scenarios two samples were collected: the mean deviance of 30 runs for the non-trading and trading case. Using an independent samples t-test the significance of the reduction in estimation deviance was shown, see Table II.

Moreover, it was found that not only does the deviance decrease under the influence of the trading algorithm, but also that PEV demand peaks shift to fixed periods during the day, namely 8:00 in the morning. The periodicity of this pattern shift is examined using a cross correlation analysis. From Figure 4 it can be concluded that there is a strong autocorrelation when the deviance is shifted 96 time steps, corresponding with a one-day shift. Moreover, correlation is slightly higher in the trading scenario, depicted in black, and

TABLE II: Mean deviance taken from Monte Carlo experiments.

Scenario	Trade [Y/N]	Mean [Wh]	Reduction	Significant
Base	No Yes	7376 7272	1.4%	Yes
Short term	No Yes	9698 9298	4.1%	Yes
Long term	No Yes	15214 13660	10.2%	Yes

TABLE III: Financials taken from short term future scenario (N = 50).

Scenario	Trade [Y/N]	Mean []	Difference	Significant
Mean costs	No Yes	1.45 1.63	12%	Yes
Max costs	No Yes	9.73 10.83	11%	No
Mean earn	No Yes	0.00 0.69	N.A.	Yes
Mean net	No Yes	1.45 0.95	-34.5%	Yes

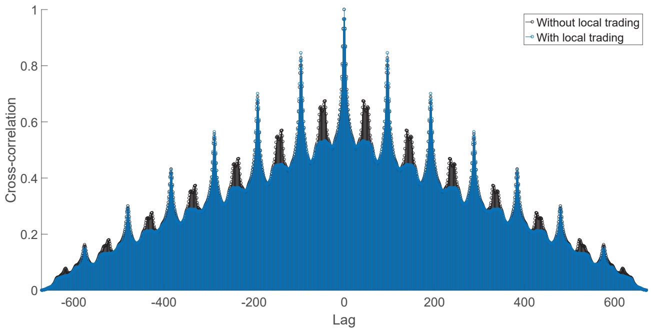

Fig. 4: Cross correlation plots of the base scenario with and without local trading.

there is less noise between one-day shifts. Therefore, it is concluded that predictable periodicity is more significantly present as a consequence of the algorithm, allowing grid operators and BRPs to more accurately estimate the PEV peak load.

Through an independent samples t-test the effect of trading on financial indicators is tested (see Table III). 30 runs of the short term future scenario are performed with and without trading, creating the two samples. The test is performed for the mean and max charging sessions cost and mean charging session earnings and net costs. The costs per charging sessions increase as a result of the algorithm. However, because the trading algorithm not only imposes smart charging, but also discharging, PEV owners can benefit from selling energy from their batteries back to the grid. As a result, the net costs show a statistically significant decrease. There is no significant effect on the maximum charging sessions costs, thus extreme costs are a result of stochastic energy demand of individual users, rather than of local trading.

Considering the nature of the input data this could be explained by the assumption of fixed tariff. The households participating in the JEM demo were incentivised to move their generation from periods with high prices to time spans with low prices. This leads to underestimation at low prices and overestimation at high prices. Due to the trading algorithm this results in PEVs charging at high prices and discharging at low prices, resulting in underestimated financial incentives for individual system users.

Figure 5 shows three battery curves, one for each of the three simulation scenarios. The curves show a recurring pattern of maximum charge in the disconnected state, a sharp decrease at arrival and between arrival and departure charging and discharging occurs interchangeably. While in the base scenario the battery is fully emptied and recharged several times overnight, the curves in the future scenarios show much milder behaviour. This is a direct result of the number of PEVs available to the grid for balancing efforts. Spread out over a larger number of batteries, the impact per individual battery is less severe. This also indicates that with an implementation in the current system, or sub-systems with low penetration of PEVs, an absolute minimum battery level should be maintained, so batteries are never empty in case of emergency trips. However, the effects on battery degradation should be explored further. Overall, the algorithm is capable of maintaining a high SOC at departure, which is shown by the following very narrow 95% confidence interval: $0.998 < \mu_{\overline{SOC}} < 0.999$. This interval was generated from 30 runs in the short term future scenario.

VI. Discussion and Future Work

We proposed a decentralised architecture that can enable local energy trade. The algorithm is able to decrease the deviance between estimation and actual consumption and thus help with load balancing in smart grids. Considering that the ABM shows that balancing efforts can amount to 25% of initial estimation, a reduction of 4.1% will have a large impact. Furthermore, the algorithm can successfully incorporate individual user preferences, such as PEV minimum SOC and financial incentives, in the allocation. This could improve the effective integration of DRs such as REG and PEVs, possibly leading to increased adoption of such technologies. In other words, the energy transition is accelerated.

The ABM covers only home-work-home trips in the case of household-owned PEVs. By stochastically assigning departure and arrival times accordingly, the resulting charging behaviour offers a good start for scenario analysis, however does not fully capture real-life charging behaviour. In future work the ABM can be expanded to cover for instance trips made by stay-at-home parents, another large PEV user group. The availability of more local storage during the day could further enhance the benefits. Moreover, it is assumed that all PEV owners partake in the system, resulting in an underestimation of the amount of PEVs that would be required for the benefits we found. A user participation questionnaire, much like those conducted for the JEM project, could provide more certainty.

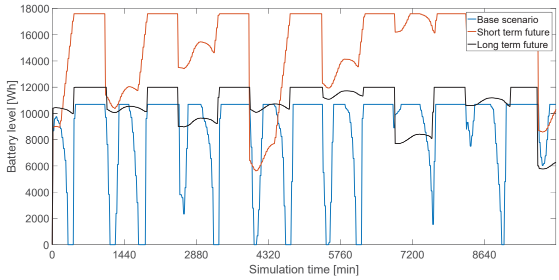

Fig. 5: Battery curves taken from base, short term, and long term future scenarios.

For simplification reasons only rooftop solar panels were included as sources of REG. In the smart grid of the future other sources, such as wind and geothermal, will make up a significant share of the total sustainable generation profile. Their output patterns are different from that of solar energy and can therefore have different effect on the performance of the proposed solution. For example, the highly variable nature of wind energy causes even more uncertainty in power management, something the local storage offered by PEVs could mitigate.

Typically, state-of-the-art energy markets do not allow for direct sales between consumers, but are only open to aggregator parties, such as BRPs, that represent them. The distributed character of the work we propose is one of its unique selling points. Therefore, future effort should focus on how a technical implementation could be achieved. At the moment we are working on an implementation of the design using blockchain technology, which promises both the required decentralised, distributed computation, as well as security of transaction validity.

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