Decarbonized Demand Response for Residential Plug-in Electric Vehicles in Smart Grids

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Abstract—Recently, in Paris, the world has reached an agreement whereby many countries commit to bolster their efforts about reducing adverse climate changes. Hence, we can expect that decarbonization will even attract more attention in different energy sectors in near future. In particular, both generation side and consumption side are required to be run more congruently and environmentally friendly. Thus, employing the renewables at the generation side along with our proposed decarbonized demand response (DDR) at the consumption side could significantly reduce deleterious impacts on the climate. Such ambition, at the consumption side, necessitates symbiosis and synergy between the customers and the retailer, and among customers, respectively. In other words, there should be some incentive-based collaboration between customers and the retailer as well as coordination among customers to make the objective be achieved successfully. In this paper, we present such matching demand response (DR) algorithm for residential users owning vehicle-to-grid (V2G) enabled plug-in electric vehicles (PEVs) who obtain electricity from a common retailer. The retailer itself is connected to the wholesale electricity market to purchase and sell electricity. Furthermore, we explain the details of the existing symbiosis and synergy in our system. Our simulation results illustrate that substantial cost savings can be achieved along with pollution reduction by our proposed technique.

Index Terms—Climate change, demand response (DR), electricity retailer, plug-in electric vehicles (PEVs), power demand elasticity, residential load, smart grids, vehicle-to-grid (V2G).

I. INTRODUCTION
Climate change has become one of the major concerns worldwide. Recently, in December 2015, many countries have agreed to further enhance their efforts to confront adverse climate changes which are mainly because of tremendous greenhouse gases (GHGs) emissions, e.g., CO₂ and CH₄ [1].

One of the significant reasons for GHG emissions is the transportation sector. Thus, decarbonization this sector has attracted much research, e.g., [2]–[6]. Meanwhile, plug-in electric vehicles (PEVs) are good alternatives for traditional cars to diminish carbon emissions provided their electricity consumption is managed properly.

However, in the literature, PEVs’ charging and/or discharging management and scheduling are mainly investigated for cost savings purposes, e.g., [7]–[10]. In these papers, the emphasis is mostly on increasing the users’ utility, welfare, the billing strategies, etc.

On the other hand, in near future, we are going to face a new paradigm in power system, e.g., new ways of electricity generation, market liberalization, storage capability, two-way electricity delivery, demand side management (DSM), demand response (DR) and environmentally conscious transportation [11] and [12]. Let us add the salience of decarbonization to the above list. Hence, a practical technique is incumbent to consider this new paradigm in order to be competent enough to be employed in a real-world smart grid.

The share of the electricity generation and transportation sectors in GHGs emissions depend on many factors, e.g., type and age of generators, different regions, traffic congestion management, etc. It varies from one region to another one in the world. For instance, Fig. 1 illustrates the GHGs emissions by sector in 2014 [13].

Fig. 1: The United States of America GHGs emissions by sector in 2014 [13].
Fig. 2: The share of GHGs emissions in the transportation sector by mode in the U.S. [13].

59%. Nonetheless, PEVs’ electricity demand adds a huge burden on the power generation side.

We should note that striving to make decarbonized energy supply alone is not adequate [14] nor is electrification of transportation sector. In order to triumph in GHGs reduction, congruous DR techniques are also needed. In other words, taking into account the level of GHGs emissions for the generation and consumption sides in DR can further diminish the emissions even in an already electrificated sector.

In this paper, we consider Pennsylvania-Jersey-Maryland (PJM) day-ahead (DA) and real-time (RT) electricity market. We use its pricing data for the years 2014 and 2015 [15], the average prices of electricity per MWh which has been sold over those two years are very close for both DA and RT markets in each year, i.e., $48.95 and $48.21, in 2014, and $33.94 and $33.34 in 2015, respectively. The reason for cheaper average price in 2015 compared to its antecedent year could be the unprecedented falling down of the oil price.

Fig. 3 shows the annual standard deviation of electricity price in 2014 and 2015 for each hour of a day in PJM for both DA and RT (spot) markets. Although the prices are much cheaper in 2015, we observe that hourly pricing data for PJM’s DA and RT markets can be significantly distinct and unpredictable. Another point is that we see RT market prices have more fluctuations than the DA market, as we could expect it. Therefore, the high uncertainty, particularly in the RT market, can remarkably affect the overall electricity procurement cost for a retailer especially in the long term. This fact is much more expected when the power system is relying on a large number of intermittent energy resources with more uncertainty.

The role of intelligence along with significant architectures and concepts in future power systems are reviewed in [16]. A good overview of DR and their different classifications in a deregulated electricity market is discussed in [17]. In [18], we present a statistical modelling and a closed-form expression for PEVs’ uncoordinated charging power demand. Our paper [9] proposes a decentralized demand shaping algorithm for an a priori known demand profile for the next day or for flattening the aggregated daily demand profile. In [10] we consider both DA and RT markets of PJM in our proposed DR algorithm.

In this paper, for the transportation sector, by adding the significance of reducing GHGs emissions, we discuss decarbonized DR (DDR) techniques for residential users owning vehicle to grid (V2G) enabled PEVs by which we strive to decrease the emissions from the electric power sector, see Fig. 1. Hence, we contemplate lessening both carbon emissions and electricity procurement costs.

II. SYSTEM MODEL

In this section, we provide the underlying model and assumptions of the power system in this paper which entails the energy markets, the electricity retailers or the aggregators, and the residential users. Similar models for future smart power systems are advocated in [8] and [19]. We discuss this model in the sequel.
Fig. 4 represents our model of a smart electricity system where multiple users share one electricity retailer or an aggregator. The users’ overall load can be differentiated into two distinct types: typical household load which normally needs on-demand electricity supply, e.g., air conditioning, heating, lighting, audio visual devices, cooking and refrigerator, and PEV as a flexible or programmable load. Here, the dotted lines show the underlying information system and the solid lines represent the power transmission and distribution infrastructure.

We assume that an electricity retailer (which may own its generation capacity) bids to the energy market, e.g., on a DA basis. Then, based on its energy needs and the market situation, it buys electricity from the market at market clearing prices (MCPs). Then, we assume that the retailer is willing to handle its customers’ PEVs’ electricity assignments (charging and discharging) such that the shape of the resulting aggregated power demand profile matches the electricity profile resulted from the successful bids in the DA market.

This enables the retailer to minimize its demand from the RT market—which has more price volatility according to Fig. [3] for balancing the load in the following day. Accordingly, it can reduce the overall electricity procurement cost. This cost reduction makes the energy retailer afford to offer more attractive deals to the customers in the form of pricing, rewarding, promotions, etc [9].

On the other hand, we assume that there are some incentives or limits from a regulator or the government which make the retailers interested in or have to reduce the GHGs emissions. We note that the incentives and limits can be translated to pay-offs and fines, in terms of fulfillment and violation, respectively. As we indicated in [10], retailers adjust their electricity deals (purchase and sell) in response to market prices. Nevertheless, the regulator can put some limits on power consumption, e.g., excessive power consumption at each time slot. This prevents the maximum power that can be delivered to/from the PEV, we may presume \( p_{\text{max}} = \omega \), and \( T_{\text{PEV}} \) describes the permissible charging time set or simply the set of time slots during the PEV’s connection time to the power grid. This is simply the set of time slots between \( \alpha_n \) and \( \beta_n \). Constraint (5) limits excessive power consumption at each time slot. This prevents the need to turn on or use traditional thermal generators.

Additionally, \( l_{-n} \) is the aggregated power profile from other \( N - 1 \) users in the system which is described as follows:

\[
l_{-n} = \sum_{i \in N, i \neq n} (l_{\text{PEV},i} + l_{A,i}).
\]
PEV’s battery lifetime due to complete depletion are avoided.

total capacity in order to make sure that the adverse impacts on PEV’s state of charge (SOC) should not fall below 20% of that and we assume that in case of employing V2G in the system, a priori, at each time slot $t$

In (8), $C_{PEV,n}$ is the total storage capacity of the user n’s PEV and we assume that in case of employing V2G in the system, PEV’s state of charge (SOC) should not fall below 20% of that total capacity in order to make sure that the adverse impacts on PEV’s battery lifetime due to complete depletion are avoided.

We know the fact that $(I^l, p^{RT})$ is unknown to the retailer a priori, at each time slot $t_0$ of the next day after getting this information, the retailer may decide to alter the previously shaped DA demand profile. It may want to minimize its RT electricity purchase to balance the load if the RT prices rise unexpectedly and even sell back some of its pre-purchased electricity from DA market to the RT market by using the PEVs’ available demand elasticity. RT prices may fluctuate significantly due to the state of the RT market or contingencies.

We should notice that in the proposed programming method $\lambda$ is one for shaping the aggregated demand profile. It may want to minimize its RT electricity purchase to balance the load if the RT prices rise unexpectedly and even sell back some of its pre-purchased electricity from DA market to the RT market by using the PEVs’ available demand elasticity. RT prices may fluctuate significantly due to the state of the RT market or contingencies.

As the chances for the price to remain that high during all the next remaining hours of the day is low [20], reshaping the load profile by lowering the electricity consumption at that time slot and purchasing electricity at the further time slots can yield to a lower electricity procurement total cost in practice. This is also true for purchasing electricity at those time slots when price, unexpectedly, falls down significantly. The retailer may buy extra electricity at those specific time slots (based on the overall storage capacity coming from connected PEVs).

We should note that the retailer is assumed to be allowed to employ the existing flexibility (offered by each user’s PEV) and the diversity (resulting from the users’ different usage patterns). We refer to these two as the system’s elasticity. Nevertheless, the electricity consumption behaviours of the users (their PEVs’ usage patterns) are not to be changed and hence the algorithm preserves users’ comfort. Moreover, users’ privacy is not violated as the information about their individual appliances, including PEV, is not revealed.

The convergence criterion in Algorithm 1 can be simply assumed as a desired number of iterations of updating all users’ demand profiles or it can be determined to be lower than some pre-set mean square error (MSE) between two subsequent iterations of achieving aggregated demand profiles. As we have discussed in [9], the convergence is guaranteed to be obtained. Furthermore, users’ contribution can be modelled as a cooperative game with complete information wherein a Nash equilibrium exists [9].

### IV. Simulation Results

In this section, we evaluate and present the results of our proposed model and programming technique articulated in the previous sections through computer simulations. In the

![Fig. 5: Distributions of (a) arrival time, (b) departure time, (c) charging time and (d) initial SOC, for 1,000 electric vehicles.](image)
simulations, we consider the number of residential users, $N$, to be 1,000 and the horizon for testing and evaluation is considered to be 24 hours for a DA programming scenario with a time granularity of one hour.

For the PEVs usage patterns, our data and distributions are based on 2009 NHTS data [21]. Fig. 5 displays the distributions for arrival time, departure time, charging time and PEVs’ state of charge (SOC) at the arrival time. Furthermore, we considered new standard outlets, NEMA 5-15, with 1.8 kW power transfer limit. We assumed that PEVs are needed to be fully charged by their respective next departure time. Additionally, we considered 24 kWh energy storage capacity for all PEVs according to Nissan Leaf model [22]. Moreover, we adopted the PJM interconnection electricity market pricing data for both DA and RT markets in the year 2015 [15] and assumed that PEVs are all V2G enabled.

Next, we examine the DDR scheme introduced in Algorithm 1. Fig. 6 shows the assumed daily aggregated electricity demand profile of the users with and without the presence of PEVs with different usage patterns based on NHTS data.

Fig. 7 shows an assumed electricity profile cleared for the retailer in the DA market. In other words, it shows the bids that could be cleared in the market at different hours of the following day. The results of Algorithm 1 is depicted in Fig. 9. For this, we assumed $\lambda = 0.5$ in (2). For a particular day as an extreme example- Fig. 8 - it can be observed that at the eighth hour of the day the highest RT price occurs. Online demand altering can reduce the aggregated demand from 1258.7 kWh to 878.2 kWh, i.e., we can obtain almost %30 reduction in the overall demand at that hour. This is when the constraint (5) in the proposed programming technique and algorithm is not complied. In case of the absence and presence of that constraint -Decarbonization constraint- DDR algorithm results can be seen in Fig. 9(c). But, the power demand at eighth hour is now 985.6 kWh which cause some extra cost. This additional money could be paid back by the regulator to the retailer as subsidies for instance.

In our simulations, convergence has been attained only after one single iteration of updating all users’ electricity demand profiles in Algorithm 1.

| Case | Energy procurement cost ($) |
|------|----------------------------|
| 1    | 5,382.3                    |
| 2    | 4,463.9                    |
| 3    | 4,149.2                    |
| 4    | 4,262.8                    |

**TABLE I: OVERALL ENERGY PROCUREMENT COSTS FOR THE RETAILER**
It should be emphasized that this could be achieved since at that hour of the day we had almost 405 V2G enabled PEVs available at users’ dwellings. Different results would be obtained for the other hours of that day. Also, it is obvious that the amount of cost savings would be dissimilar on weekdays and in the weekend.

In Table I, we compare the overall electricity procurement costs for the retailer for four cases: case (1) is purchasing electricity without any DR, case (2) when DR technique in [9] is used, i.e., only DA demand shaping is implemented, case (3) when joint shaping and altering demand is applied as in [10] and case (4) when DDR is being employed.

It can be seen that in the first case, when no DR method is used and the power demand is directly purchased from the RT market, total cost is the highest. For the second case, around $920 is saved and in the third case the cost is further reduced by $314.7. In the fourth case, however, when DDR is employed there is some extra cost, $113.6, because of complying with the GHGs emissions reduction in Algorithm 1.

V. CONCLUSION AND FUTURE WORK

In this paper, we proposed a fast converging and decentralized algorithm for managing V2G enabled PEVs’ electricity assignments (charging and discharging) in order to simultaneously reduce the overall electricity procurement cost and GHGs emission for electricity retailers. We illustrated that with some incentives and/or regulations from the regulator, the retailer or aggregator could help lessening GHGs emissions by using our proposed decarbonized demand response (DDR) technique.

In this work, we emphasized on the importance of considering decarbonization in DR algorithms for PEVs. However, various other combinatorial optimization methods could be investigated. Furthermore, regional GHGs emission factors can be captured into the evaluations in practice.

REFERENCES

[1] E. Burleson, “Paris agreement and consensus to address climate challenge,” ASIL INSIGHT, Forthcoming, 2016.
[2] H. Zhang, W. Chen, and W. Huang, “Times modelling of transport sector in china and usa: Comparisons from a decarbonization perspective,” Applied Energy, vol. 162, pp. 1505–1514, 2016.
[3] K. C. Hargroves, C. Desha, and E. von Weisaeker, “Introducing carbon structural adjustment: energy productivity and decarbonization of the global economy,” Wiley Interdisciplinary Reviews: Energy and Environment, vol. 5, no. 1, pp. 57–67, 2016. [Online]. Available: http://dx.doi.org/10.1002/wene.181
[4] J. Liu and G. Santos, “Decarbonizing the road transport sector: break-even point and consequent potential consumers’ behavior for the us case,” International Journal of Sustainable Transportation, vol. 9, no. 3, pp. 159–175, 2015.
[5] K. B. Abdallah, M. Belloumi, and D. De Wolf, “International comparisons of energy and environmental efficiency in the road transport sector,” Energy, vol. 93, pp. 2087–2101, 2015.
[6] S. Mittal, H. Dai, and P. Shukla, “Low carbon urban transport scenarios for china and india: A comparative assessment,” Transportation Research Part D: Transport and Environment, 2015.
[7] B. G. Kim, S. Ren, M. van der Schara, and J. W. Lee, “Bidirectional energy trading and residential load scheduling with electric vehicles in the smart grid,” IEEE Journal on Selected Areas in Communications, vol. 31, no. 7, pp. 1219–1234, Jul. 2013.
[8] A. H. Mohsenian-Rad, V. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, “Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid,” IEEE Transactions on Smart Grid, vol. 1, no. 3, pp. 320–331, Dec. 2010.
[9] F. Rassaei, W. S. Soh, and K. C. Chua, “Demand response for residential electric vehicles with random usage patterns in smart grids,” Sustainable Energy, IEEE Transactions on, vol. 6, no. 4, pp. 1367–1376, Oct 2015.
[10] ———, “Joint shaping and altering the demand profile by residential plug-in electric vehicles for forward and spot markets in smart grids,” in Smart Grid Technologies - Asia (ISGT ASIA), 2015 IEEE Innovative, Nov 2015, pp. 1–6.
[11] C. Marnay, “Challenges of supply: An evolving energy paradigm [in my view],” Power and Energy Magazine, IEEE, vol. 11, no. 5, pp. 104–100, 2013.
[12] M. Katz, Environmentally conscious transportation. Wiley Online Library, 2008, vol. 1.
[13] Center for climate change and energy solutions. [Online]. Available: http://www.c2es.org/facts-figures/us-emissions.
[14] J. H. Williams, A. DeBenedictis, R. Ghanadan, A. Mahone, J. Moore, W. R. Morrow, S. Price, and M. S. Torn, “The technology path to deep greenhouse gas emissions cuts by 2050: the pivotal role of electricity,” Science, vol. 335, no. 6064, pp. 53–59, 2012.
[15] Pennsylvania-jersey-maryland (PJM) interconnection. [Online]. Available: http://www.pjm.com/marketdata/markets-and-operationsoptools/data-miner.aspx.
[16] T. Strasser, F. Andreu, J. Kathan, C. Cecati, C. Bucchella, P. Siano, P. Leitao, G. Zhabelova, V. Vyatkin, P. Vrba et al., “A review of architectures and concepts for intelligence in future electric energy systems,” Industrial Electronics, IEEE Transactions on, vol. 62, no. 4, pp. 2424–2438, 2015.
[17] M. H. Albadi and E. El-Saadany, “A summary of demand response in electricity markets,” Electric Power Systems Research, vol. 78, no. 11, pp. 1989–1996, 2008.
[18] F. Rassaei, W. S. Soh, and K. C. Chua, “A statistical modelling and analysis of residential electric vehicles’ charging demand in smart grids,” in *Innovative Smart Grid Technologies Conference (ISGT), 2015 IEEE Power Energy Society*, Feb 2015, pp. 1–5.

[19] Y. Liu, C. Yuen, S. Huang, N. Ul Hassan, X. Wang, and S. Xie, “Peak-to-average ratio constrained demand-side management with consumer’s preference in residential smart grid,” *Selected Topics in Signal Processing, IEEE Journal of*, vol. 8, no. 6, pp. 1084–1097, Dec 2014.

[20] J. M. Poterba and L. H. Summers, “Mean reversion in stock prices: Evidence and implications,” *Journal of financial economics*, vol. 22, no. 1, pp. 27–59, 1988.

[21] National household travel survey (2009). [Online]. Available: [http://nhts.ornl.gov](http://nhts.ornl.gov).

[22] Nissan Leaf. [Online]. Available: [http://www.nissanusa.com/electric-cars/leaf](http://www.nissanusa.com/electric-cars/leaf).