

Charging Optimization of Enterprise Electric Vehicles for Participation in Demand Response

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Abstract—In the emerging smart grid, using flexible infrastructures to realize better energy management via demand response scenarios is at its core. The potential of electric vehicles used to realize such flexibility is widely experimented with. In this work, we take a closer look at a specific case of enterprise-owned electric vehicles, parked at enterprise premises, and how their charging can be optimized in order to both adhere to the enterprise operational constraints, as well as consider dynamic changes stemming from other grid stakeholders. A simplified optimization using an evolutionary algorithm is realized, and the approach is evaluated under two scenarios of interest.

Index Terms—Energy Management; Smart Grids; Optimization; Renewable Energy Sources; Supply and Demand; Electric Vehicles; Cost Function; Load Management

I. MOTIVATION

Significant efforts [1] have been devoted the last years towards exploring the new capabilities offered by the smart grid and how to grasp its benefits. Of special interest are the cases devoted to Demand Side Management (DSM) and especially Demand Response (DR) [2] which now can be realized in a better way as well as in large scale with tangible benefits [3]. Such scenarios are empowered by bidirectional interactions among the legacy and emerging smart grid stakeholders [4], over a standardized infrastructure [5].

Of specific interest to the many smart grid stakeholders are the DR scenarios [4], as these can yield additional (usually monetary) benefits to the involved stakeholders, while in parallel tackling key problems in the grid due to highly dynamic energy production stemming from Renewable Energy Sources (RES). The role of the Electric Vehicles (EVs) in smart grid is increasingly investigated [6], including their utilization as dynamic storage [7], since, if a critical mass of them is reached, they can have a significant energy impact on existing infrastructure, future planning and naturally in any energy optimization scenario.

EVs can be an active participant in DR, since they provide flexibility during longer standing times. This is especially of interest when larger numbers of them are available, which is the case e.g., for EV fleets. Several uncertainties are coupled with individual EVs including, their presence, the authorization to centrally control charging, the acceptance by the consumer (EV owner), the impact on the EV battery, etc. However, many of these considerations, can be set aside in specific cases, such as those involving enterprise-owned cars.

In this work we focus on this area and introduce two DR scenarios (a price-based and an incentive-based one) that are attractive for enterprise fleets of electric vehicles. The latter can react to DR events, with the flexibility given by long and predictable parking times without interfering with their operational plan. We introduce an optimization approach that allows operators of such EV fleets to react to two different types of DR events. Finally we evaluate these two scenarios and the optimization realized, with real world data both for available RES and enterprise EV fleet.

II. DEMAND RESPONSE FOR DSO AND SUPPLIERS

In the context of enterprise-owned EVs, different motivations exist for shifting electrical loads over time. From a local point of view, such load shifts can help reducing consumption (due to EV charging) at times where electricity is expensive in order to reduce overall enterprise costs. In addition, EVs can also be used to prevent the overall power draw from exceeding technical or contractual limitations which could lead to physical damages or penalty fees. DR allows extending this concept from local boundary conditions to more global aspects, as due to the bi-directional communication among the involved stakeholders, other parties such as energy suppliers and grid operators can influence consumers in order to make them shift their loads in a specific manner, and result to tangible benefits for all.

A prerequisite for demand response is a standardized communication between the involved energy market participants. Since the grid operator usually doesn't interact directly with consumers, the energy supplier in our scenarios can be seen in the central role of a demand response provider and aggregator. A supplier knows his consumers since he has contracts with them and usually also has detailed analytics on their energy behavioral patterns. In this work, we consider two types of DR scenarios i.e., price-based DR for suppliers and incentive-based DR for grid operators or other energy market participants.

A. Price-Based Demand Response

Price-based demand response uses short term price shifts in order to influence the power consumption at a given point in the near future. By increasing the price, demand can be reduced and vice versa. Price-based DR can therefore be used by suppliers to increase or decrease their customers' demand in order to meet their market predictions and avoid buying

expensive balancing energy. The advantage of this DR type is its simplicity, while its drawback is the fact that the supplier cannot exactly predict the individual consumer behavior. As such, customers could e.g., accept a higher price without changing their behavior when a reaction is inconvenient for them. In order to not entirely compromise the customer planning security, some restrictions are put in place.

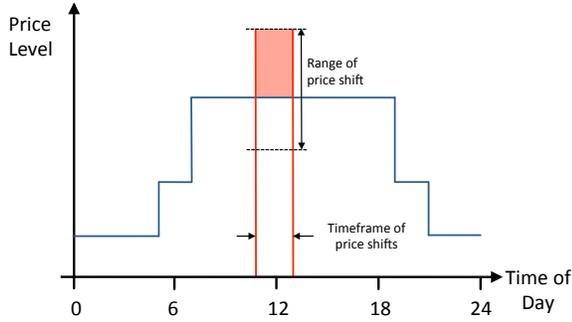


Figure 1. Example for price based DR

The price-based demand response could potentially be more customer-friendly if it is bound to predefined time- and price-frames and if only a limited number of events per year are allowed. These limitations may lead to more trust from the customer side than frequent dynamic changes from the energy market, and therefore there might be a higher chance for customer acceptance and participation in such schemes. We consider that for success, such adjustments must be non-intrusive, require no additional customer-interaction, and respect fully constraints set by them. Such details could be specified in the contract between supplier and consumer. The execution of price-based demand response is simple; when the supplier detects an upcoming mismatch between the energy he purchased for a given time frame and the predicted demand of his customers, he can increase or decrease the energy price within that time frame for all participating customers (as exemplified in Figure 1). The latter could be done for specific targeted groups based on several criteria e.g., in a specific location, capability to react quickly and at mass, prior adherence to similar events, flexibility etc.

B. Incentive Based Demand Response

The incentive-based demand response we investigate, represents a tool for grid operators that they can use to reduce power consumption in a specific grid area in order to avoid overloads. Since grid-operators generally do not have direct contracts with consumers and therefore cannot directly influence the price, this type of DR is more complex than price-based demand response. It must also be considered, that a direct influence of the consumer behavior might harm the supplier who has to meet the predictions for his balance group in order to avoid penalty fees. Therefore, a way needs to be found that involves energy suppliers, when a grid operator wants to influence the demand in a grid sector. For grid operators, shifting the demand is of high priority, especially when the grid load risks reaching the grid capacity. In this context, grid

operators like EnBW in Germany, talk about a so called grid traffic light that distinguishes between three phases:

- **Green:** The grid load is far below the maximum grid capacity. No action is needed.
- **Yellow:** The grid load is near the maximum grid capacity but has not yet reached it. To avoid possible outages due to a further increase of the load, incentive based demand response can be used in order to lower the demand.
- **Red:** The load has reached the maximum grid capacity and the grid operator is forced to separate single consumers from the grid in order to avoid severe general outages and to restore the grid stability.

Incentive-based demand response is mostly interesting during the yellow phase, when all possible measures have to be taken to avoid the red phase. It allows to figure out for which consumers a load reduction causes less disadvantages and costs. Separating consumers from the grid in the red phase affects (usually arbitrarily) consumers, it may lead to physical damages to their infrastructure (like e.g., electric vehicles) and does therefore not represent a valuable substitute to DR. Furthermore in cases of EV fleets controlling the grid capacity by secondary actors without the agreement of the fleet operator could lead to violations of the operational plan. The reduction of available capacity or cutting it off completely can delay the charging of EVs that are needed in business operations and lead to additional business cost for the operating enterprise. The incentive-based demand response avoids this by respecting the operational plan and the business usage of the EVs, and only uses the flexibility given by that schedule.

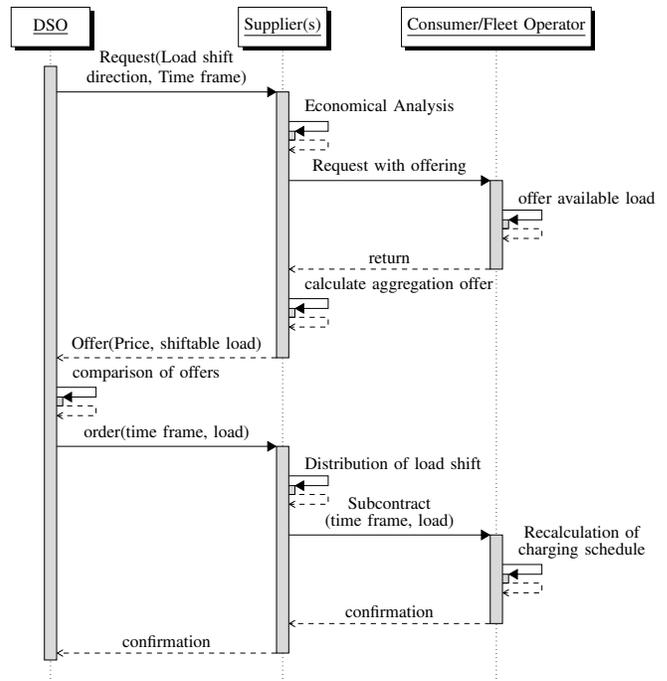


Figure 2. Overview of stakeholder interactions in incentive-based DR

Based on the capabilities offered by the smart grid, and especially due to the bidirectional communication among

the stakeholders, a negotiation can take place. As shown in Figure 2, an incentive-based DR that involves both the grid operator and different suppliers can be executed. When a grid-operator wants to reduce the demand in a grid-sector, he can send a request to the suppliers who have customers in the respective grid segment. The request should include the time frame for which a load reduction is desired.

A supplier who receives such a request will analyze it and under consideration of all boundary conditions and costs he can calculate incentives (e.g., € per reduced kW) he can pay to customers who are willing to adjust their future load in the respective time frame. The supplier sends this incentive offer to all his customers among which in our case we have an operator of an electric EV pool (fleet manager). Considering the incentive, the fleet operator calculates how much load he is willing to shift and communicates this to his supplier. As a follow-up, the supplier aggregates all load shifts that his customer(s) have agreed upon, and under consideration of all his costs he makes an offer to the grid operator.

The grid operator compares the offers of the different suppliers and those who made the best offer will receive a request which specifies how many kW the overall load of their customers should be reduced. Finally, the supplier calculates internally how to distribute this request and redirects the requests to his customers. Due to the technical restrictions of the EVs and the charging stations, especially the maximum and minimum charging power, not every arbitrary load shift request can be implemented by the EV fleet. Therefore the optimization calculates the closest possible value to this requested load shift. This small difference is then communicated in the confirmation, and at aggregated level is usually insignificant.

III. OPTIMIZING EV CHARGING FOR DR PARTICIPATION

Many enterprises today provide as a benefit to their employees cars, and increasingly these cars are EVs. While these EVs are used by the employees both for business and private utilization, their lifecycle activities are managed by the respective enterprise team. Practically this implies that some considerations such as the impact on the EV battery, the acceptance by the EV owner etc. are no longer an issue.

In addition, the presence of these EVs is highly correlated to the work schedule of the respective employee and this can be highly predictable or derived from other sources (e.g., employee calendar, vacation application, business meetings etc.). During the charging of the EV at enterprise premises, which in practice might resolve to approx. 08:00–17:00 timeframe, the EV as well as its charging are under the control of the enterprise and as such, centrally planned optimization can be realized and enforced.

Such optimizations however, have to consider not only enterprise needs and benefits, but also comply to the consumer needs and plans for the rest of the day. So the result is a multi-constrained optimization that needs to consider the varying needs of the involved stakeholders (described as constraints) as well as being able to accommodate dynamic changes to these constraints.

If a critical mass of EVs is reached, they can have a significant impact on energy optimization scenarios. Uncoordinated charging load of electric vehicles may increase peak loads of the power grid. A “valley-filling” charging scenario offers a cheap approach [8], however it is not always applicable to dynamic changes especially in short time frames. With the appropriate strategy EVs may charge while keeping the peak demand unchanged [6]. Tangible benefits can stem from DR programs as well as potential cost savings and benefits related to different market components concluded with a selected DR-experiment carried out by a utility [9].

In this work, we focus on real-world cases for enterprise owned EVs that charge at work premises, which overcomes some limitations and uncertainties coupled to EV presence, the authorization to centrally control charging, the acceptance by the consumer (EV owner), the impact on the EV battery, etc. In the enterprise context, users have to book the fleet EVs in advance to ensure a charged battery at their departure time. This allows the operator to create an operation plan which can be considered as reliable for a participation in DR events. To calculate the initial charging plan, as well as to accommodate recalculations due to dynamic changes dictated by DR events, we use an evolutionary algorithm which we will shortly describe in the next section. A description of the mathematical model and the algorithm in more details can be found in [10].

A. EV Charging Optimization Algorithm

For the optimization algorithm there are hard constraints, which must not be violated. These include the grid capacity and the charging power constraint. The latter include the charging stations and the EV’s minimum and maximum charging power of both, or is 0. The soft constraints contextualize the desired state of charge at the end of the charging process. If not enough capacity is available, the desired energy amount of some EVs will not be reached or EVs scheduled for charging have to be rejected. An evolutionary algorithm is used to generate an intelligent charging plan considering grid capacity and energy price as discrete function with 15 minutes time intervals.

The representation of a solution was chosen to be the permutation of EVs, while for each EVs additionally a maximum charging power is set. This maximum charging power differs from the technical restriction, in the way that it is chosen randomly among the restrictions given by the EV and the charging station.

Each EV then gets optimized with a greedy approach, considering its new given maximum charging power and for the following fitness evaluation the overall costs of each solution are calculated, including the energy price combined with penalty costs for the violations of soft constraints.

B. Experimental Setting

The first task of the energy management system responsible within which also the charging optimization functionality lies, is to avoid violation of the load limits, respect the technical

restrictions of each EV, and minimize the energy costs. To do so, it has to calculate the optimal charging plan for each EV with respect to the cost for the entire fleet. Necessary data from the energy market, the EV and the pool fleet operator is collected e.g., from the technical parameters of each EV, the (forecasted) electricity price curve, as well as the load limitations for a specific period of time e.g., 24 hours. The operation plan, as well as the desired energy for each pool EV, is posed by the employees who book the respective EVs in 24 hours in advance for business use, in order to guarantee that the EV is charged for the planned trip on the next day.

Based on the available data the evolutionary algorithm calculates a cost optimal charging plan for the fleet, that respects the aforementioned constraints. The resulting charging plan is then communicated to the charging stations, which enforce it and control the charging of the EVs. Since the data from the energy market is communicated in advance, dynamic changes may appear while a charging plan is executed. To address these changes we use DR events, as depicted in Figure 2. After each event the algorithm will calculate a new charging profile starting in the next 15 min interval after the actualization.

To evaluate a possible reaction to such DR events, we look at a simulated pool of EVs owned by the enterprise and used by employees. These EVs are charged at the enterprise premises and the total cost for charging is paid by the pool fleet operator. This means that the goal of cost optimization is reducing the overall cost for the EV charging and not necessarily that of individual EVs.

The simulation is based on real-world data that has been collected by the Future Fleet project in Germany. From the collected data we did not consider the sessions that were longer than one day or shorter than one minute. For the wind scenarios we chose 50 charging sessions randomly, while for the solar scenario 50 charging sessions that occur in daytime have been selected randomly. In this way we created an operation plan for one day. In the Future Fleet project only one vehicle type i.e., STROMOS from the company German E-CARS, has been used. Since today's scenarios usually involve different EV types, we carry out the simulation on EVs with different battery capacities as well as charging powers and therefore assume the following vehicle types:

- 17 Renault Zoe with battery capacity of 22 kWh, a minimum charging power of 7.6 kW and a maximum charging power of 22 kW,
- 12 BMW i3 with battery capacity of 19 kWh, a minimum charging power of 1.38 kW and a maximum charging power of 7.36 kW,
- 5 e-Smart with battery capacity of 19 kWh, a minimum charging power of 1.38 kW and a maximum charging power of 3.68 kW,
- 16 Mercedes-Benz A-Class E-CELL with battery capacity of 36 kWh, a minimum charging power of 2.76 kW and a maximum charging power of 7.36 kW.

These are not the original EVs that were used in the German Future Fleet project; however their characteristics are included in the simulation, and are fit for our goal of simulating a

broader and more diverse spectrum of EVs with different battery capacities and charging power. The values for the battery capacities and the charging power are oriented at the values given in the EV specifications, as well as the measured values from test with this vehicles. As a delimitation, we intentionally simplify the potential constrains and do not consider the impact on the EVs e.g., overcharging of EVs, battery degradation [11] etc. Such fine-grained considerations are left for future work.

To apply realistic boundary conditions to this scenario, data from renewable energy sources like solar and wind is used. These datasets for wind and solar refer to a single location in Spain as collected by the NOBEL project platform [12]. For solar we arbitrary selected the production data of the 06-Jun-2012. To calculate the energy production from the wind data, we used the model for the "Tornado 1 kW" turbine. According to [13] there are regions in Spain where the mean wind speed lies between 4 and 5 m/s such as the region close to the NOBEL trial from where we have the field data. The dataset we used in our evaluation resulted in an average wind speed of 4.76 m/s. For the evaluation, the arbitrary example 03-Oct-2013 from the dataset was chosen.

All company pool EVs are treated equally and it is considered that the pool fleet operator can send a charging plan to each EV to control the charging within the given flexibility. This charging plan has to ensure that all EVs are charged at least to the level that fulfills the wishes of the next reservation (i.e., respect consumer constraints); otherwise the employee would not be able to meet the next appointment, which is not acceptable business-wise.

If charging is possible, then in most cases there exists for each EV i during the standing time T_i an infinite number of valid charging functions L_i^j , that fulfill the condition to charge the desired energy amount. The potential for load shift is then given as the union of all these valid charging functions $\bigcup_j L_i^j$. The load shift potential is given as the boundary of this set. For a positive load shift it is the charging plan with the lowest charged energy, while for negative load shift it is the one with the highest possible charging energy in a certain time interval.

IV. EVALUATION

For the parameters used in the algorithm, a standard suggestion is used [14], advising that the population size should lie between 1 and 30 solutions, and that the best selection for the quotient between parent solutions and number of solutions in the evaluation of the fitness has a value between $\frac{1}{5}$ and $\frac{1}{7}$. In our case this leads to a start population of 20 solutions, and in each evolution process 40 child individuals are generated via recombination and another 40 child individuals are generated via mutation. For the next generation the 20 best solutions are selected and is repeated for a certain number of generations.

We evaluated the algorithm according to its run time and improvement of the fitness function by stepwise increasing the number of generations. The critical point is the feasibility for the chosen scenarios, like calculating a charging plan and

reaction to demand response events like short term changes in price curve or request for load shifts.

The experiments show that for all three scenarios the first populations tend to start with a poor fitness (as expected) which significantly changes within the first 5–10 generations. Afterwards, the fitness increases only minimally over the next approximately 500 generations. In the majority of experiments (20 for each scenario) the fitness does not noticeably change (less than 0,1%) after the 500th–1000th generation. The execution time for the algorithm with 500 generations is less than 20 seconds, which evidences that even with this number of generations the algorithm is still fast enough to quickly react to time-sensitive DR requests.

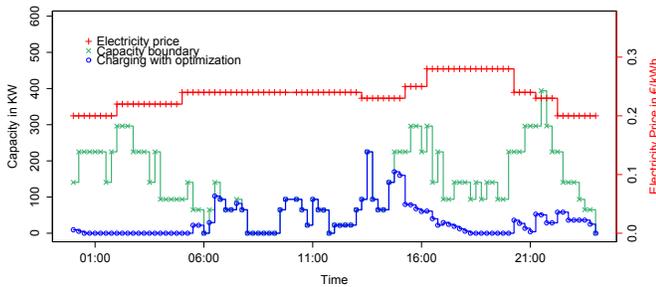


Figure 3. Charging plan for a company pool fleet of 50 EVs with restricted capacity due to limited wind production

In our scenario we consider energy supplier and grid provider as two independent stakeholders. Therefore the price profile (denoted by a red line in the figures) is not necessarily correlated to the wind profile, even though in future, especially in DR scenarios, this might be increasingly the case. This scenario shows that the algorithm can handle both possibilities. The first priority is to respect the capacity restriction which is not necessarily the physical grid restriction, it can also be the limit given by renewable production. With the flexibility which is given (under these restrictions) the algorithm chooses the best and cheapest solution for the EV fleet.

This set-up allows the EV fleet operator to negotiate in the future a preferential contract with the supplier for a better energy price. Furthermore the EV fleet operator may couple such actions with its corporate social responsibility (CSR) and sustainability goals e.g., lowering its CO_2 emissions by charging the EVs only when energy from RES is available. Another possibility would be that the grid provider is the owner of the wind farm and aims at absorbing the maximum available RES energy generated before deciding on interacting with other stakeholders [15].

Figure 3 depicts a charging plan (in blue) that has been calculated by the algorithm for a company EV pool fleet of 50 EVs. The green curve shows the available energy calculated from wind data from the 03-Oct-2013. As depicted in Figure 3, the production capacity limit is respected, and additionally the charging is happening during the lowest costs (price curve shown in red) slot, which implies lower overall cost for charging the whole fleet.

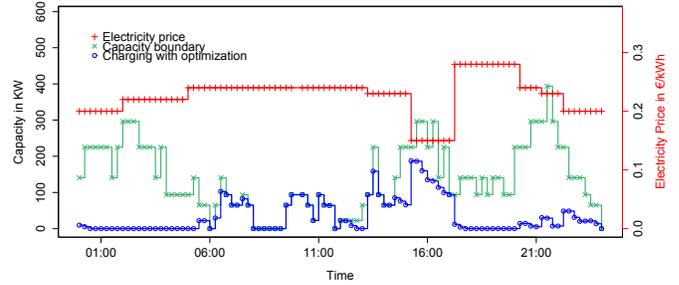


Figure 4. Charging plan for a company pool fleet of 50 EVs with restricted capacity due to limited wind production with price based demand response

The reaction of a price based demand response scenario is visualized in Figure 4. The price profile is updated between 15:00–17:00, since the energy supplier gives (four hours in advance) an incentive to consume more energy during this time interval. With this updated price profile a recalculation of the charging plan is initialized and after a short run time the new charging plan is in place. The figure visualizes that the algorithm successfully shifts consumption after the notification to the cheap DR time slot, which was originally planned to be charged in other time slots.

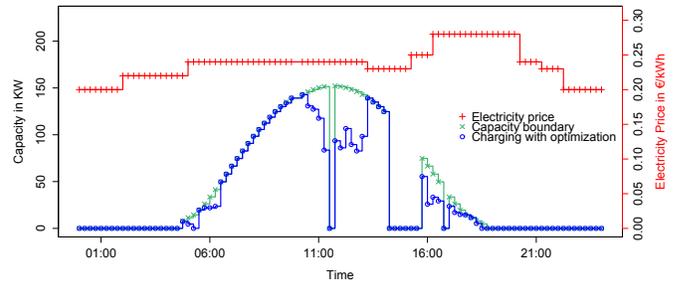


Figure 5. Charging plan for a company pool fleet of 50 EVs with restricted capacity due to limited solar production

Figure 5 depicts our experiments while considering solar production. As it can be seen, the capacity boundary is now determined by the solar production. We observe that the consumption follows the production with respect to the optimization of EV charging i.e., the EVs are charged when a surplus of solar electricity is available and stop charging when there is no production. Furthermore the cheapest time slots with available solar production are selected by the algorithm. In Figure 5 we see the charging plan which was calculated with prior communicated solar production.

Our available data from Spain usually depict a perfect Gaussian curve, except from the case depicted in Figure 5 which denotes a disruption event at 11:00 and again approx. 14:00–16:00, during which the solar generated power is not fed into the network and hence is not available for charging EVs. Although we do not know the source of this event (e.g., if it was a planned maintenance etc), such events may come well in advance from other enterprise systems (e.g., asset management system if planned), or may be identified

at the time of happening (in real-time). Our aim was to show that such events can also be dynamically integrated and compensated for by simplified and timely re-optimization of the EV charging planning.

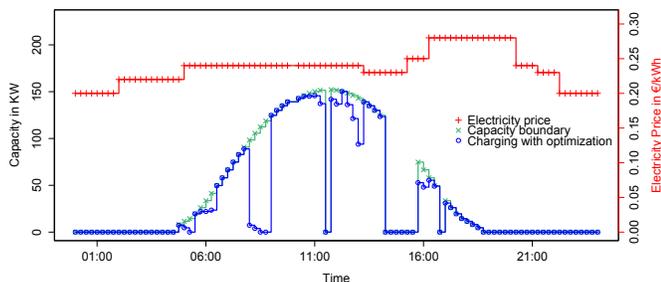


Figure 6. Charging plan for a company pool fleet of 50 EVs with restricted capacity due to limited solar production with capacity based demand response

Due to the aforementioned events a capacity based DR was triggered, one minute before the event, with the request for positive load shift in the time frame from 8:00–9:00. The algorithm calculates within seconds a new charging plan and shifts the missing load to later times. The new charging plan is shown in Figure 6 and the EV fleet operator can offer the energy market a load shift of 105 kWh.

It is worth noticing, that the algorithm only decides to shift the load completely when this will not lead to violation of the operational plan. The short run time of the algorithm shows that it can react to dynamic changes.

V. CONCLUSION

In this work we have taken a look at two DR scenarios that are of interest to enterprises operating EVs and wish to participate to DR. A simplified optimization plan is generated by an evolutionary algorithm that considers multiple constraints stemming from the involved stakeholders. The algorithm could also be executed with a less elitist selection strategy like "roulette wheel" or "tournament selection" to increase diversification in the population which could possibly lead to better results. In various experiments with solar and wind power generation, the algorithm is capable of adjusting the charging plan in seconds, which in turn makes it possible to participate in DR events and provide shiftable load to the energy market without interfering with the business usage of the EV fleet. In future enterprises, overall optimization of assets at large, including EV fleets, to adhere to enterprise policies, as well as other operational and cost constraints will be of increasing interest. The latter is due to the new capabilities of near real-time monitoring and control of the assets (such as the EVs), as well as the bidirectional interactions among the smart grid stakeholders as we have investigated. The results may yield tangible benefits for all stakeholders, and hence there is both technical and business interest for their assessment. Future steps in this direction could be experiments with larger EV fleets, while considering more fine-grained constraints and economic objectives.

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REFERENCES

- [1] V. Giordano, A. Meletiou, C. F. Covrig, A. Mengolini, M. Ardelean, G. Fulli, M. S. Jiménez, and C. Filiou, "Smart Grid projects in Europe: Lessons learned and current developments 2012 update," Joint Research Center of the European Commission, JRC79219, 2013.
- [2] J. Torriti, M. G. Hassan, and M. Leach, "Demand response experience in europe: Policies, programmes and implementation," *Energy*, vol. 35, no. 4, pp. 1575 – 1583, 2010.
- [3] US DoE, "Benefits of demand response in electricity markets and recommendations for achieving them," US Department of Energy, Tech. Rep., Feb. 2006. [Online]. Available: http://energy.gov/sites/prod/files/oeprod/DocumentsandMedia/DOE_Benefits_of_Demand_Response_in_Electricity_Markets_and_Recommendations_for_Achieving_Them_Report_to_Congress.pdf
- [4] S. Karnouskos, "Demand side management via prosumer interactions in a smart city energy marketplace," in *IEEE International Conference on Innovative Smart Grid Technologies (ISGT 2011), Manchester, UK*, Dec. 5–7 2011.
- [5] NIST, "NIST framework and roadmap for smart grid interoperability standards," Office of the National Coordinator for Smart Grid Interoperability, National Institute of Standards and Technology (NIST), U.S. Department of Commerce, Tech. Rep. NIST Special Publication 1108, Jan. 2010. [Online]. Available: http://www.nist.gov/public_affairs/releases/upload/smartgrid_interoperability_final.pdf
- [6] S. Shao, M. Pipattanasomporn, and S. Rahman, "Grid integration of electric vehicles and demand response with customer choice," *Smart Grid, IEEE Transactions on*, vol. 3, no. 1, pp. 543–550, March 2012.
- [7] S. Detzler, D. Ilić, S. Karnouskos, and C. Kindermann, "Investigating Electric Vehicles as a Promising Alternative to Static Storage Solutions," in *IEEE International Electric Vehicle Conference (IEVC), Florence, Italy*, 17–19 Dec. 2014.
- [8] K. Zhang, L. Xu, M. Ouyang, H. Wang, L. Lu, J. Li, and Z. Li, "Optimal decentralized valley-filling charging strategy for electric vehicles," *Energy Conversion and Management*, vol. 78, pp. 537–550, 2014.
- [9] 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.
- [10] S. Detzler and S. Karnouskos, "A model and an evolutionary algorithmic approach towards optimization of electric vehicle fleet charging," in *International Symposium on Smart Electric Distribution Systems and Technologies (EDST), Vienna, Austria*, 8–11 Sep. 2015.
- [11] S. B. Peterson, "Plug-in hybrid electric vehicles: battery degradation, grid support, emissions, and battery size tradeoffs," Ph.D. dissertation, Carnegie Mellon University, May 2012.
- [12] S. Karnouskos, P. Goncalves Da Silva, and D. Ilić, "Energy services for the smart grid city," in *6th IEEE International Conference on Digital Ecosystem Technologies – Complex Environment Engineering (IEEE DEST-CEE), Campione d'Italia, Italy*, Jun. 2012.
- [13] M. Gastón, E. Pascal, L. Frías, I. Martí, U. Irigoyen, E. Cantero, S. Lozano, and Y. Loureiro, "Wind resources map of Spain at mesoscale. methodology and validation," in *Proceedings of European Wind Energy Conference*, 2008.
- [14] K. Weicker, *Evolutionäre Algorithmen*. Springer-Verlag, 2007.
- [15] D. Ilić, S. Karnouskos, P. Goncalves Da Silva, and S. Detzler, "A system for enabling facility management to achieve deterministic energy behaviour in the smart grid era," in *3rd International Conference on Smart Grids and Green IT Systems (SmartGreens), Barcelona, Spain*, 3–4 Apr. 2014.