A Model and an Evolutionary Algorithmic Approach Towards Optimization of Electric Vehicle Fleet Charging

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***Abstract*—The prevalence of the Smart Grid and its capabilities, has enabled sophisticated energy management that can be realized as a multi-constraint optimization problem and tailored to the specific scenario needs. In conjunction with the increasing introduction of Electric Vehicles (EVs), energy management tools can now consider expanded conditions including grid balance, cost optimization, EV characteristics, asset utilization, operational goals etc. In this work we analyze such a scenario and demonstrate how an EV fleet charging can be optimized in a timely manner while taking into consideration local conditions e.g., individual EV needs as well as global ones e.g., grid limits and energy price. We formalize a model that reflects the EV restrictions, and use it to assess an algorithmic approach that solves this non-linear optimization problem.**

***Index Terms*—Energy management; Smart grids; Mathematical model; Renewable energy sources; Optimization; Electric Vehicles; Cost function; Load management**

I. Introduction

In the Smart Grid era, increased capabilities for monitoring and controlling energy-related assets [1], are expected to act as enablers for sophisticated scenarios. Being able to monitor in detail large-scale infrastructures, assessing complex conditions and applying control actions with feedback loops in near real-time, has the potential to revolutionize decision making processes. The latter can now dynamically adapt to new conditions, while considering complex technical and business constraints at an unprecedented level. Asset flexibility is especially important in the Smart Grid as it can balance the highly dynamic Renewable Energy Resources (RES) produced energy patterns. In such flexible energy infrastructures [2], company assets as well as larger infrastructures can dynamically adjust and be optimized with multiple goals of energy efficiency, cost reduction, operational goals etc.

A category of assets that fit very well to energy management scenarios is that of Electric Vehicles (EV) which although still at their dawn, are expected to have a significant impact once a critical mass of them is available. Due to their flexibility in charging and discharging, EVs can play the role of flexible controllable assets [2], and pose a cost-effective alternative to existing solutions for storing energy [3]. Companies that will be operating larger numbers of them i.e., in EV fleets, will have to make considerations about how to reach their operational goals while considering cost-effective approaches to fleet charging and operation. As such multi-constraint optimizations are sought, that will not only consider constraints and goals but also provide effective solutions in deterministic manner. The latter implies real-world acceptable solutions (which may be near to optimal ones but not necessarily optimal) that enable an enterprise to achieve its objectives as good as possible.

The architecture of an energy management system that takes into consideration many of these aspects has already been proposed [4]. We take this as a starting point, and focus in this work explicitly on the effort to achieve real-world optimal charging of EVs, by considering constraints such as the grid capacity, electricity price, and fleet operational utilization plan. Our aim is to reach a nearly optimal charging plan, that can dynamically adapt to adjustments of the external constraints (electricity price, EV presence, grid capacity) in a timely manner and with minimal user input. Complying with constraints specified by the EVs and by their operational utilization plan, the charging sessions are planned with the specified degrees of freedom that dictate the available flexibility we can capitalize upon.

The approach results in solving a multi-constrained optimization problem, that should deliver a highly optimized and realistic charging plan within the specific time-constraints. The problem is formulated as a load management system that leads to a mixed integer non-linear programming problem, and an evolutionary algorithm is introduced to solve it. Subsequently the evolutionary algorithm is assessed for a use case of a typical EV fleet.

II. Model Description

To describe the charging plan of a fleet of electric vehicles, we first need to investigate how the charging plan of an single EV can be adequately modeled. The charging functions considered in this model are discrete, which means that each time interval has a constant charging power. Such function are Lebesgue integrable, therefore we use the mathematical construction of Lebesgue integrals for the description of the model. The Lebesgue integral is defined for a measure space which is a set Ω with a structure that allows to map a certain subset to a measure, like its geometrical length. This measurement is called Lebesgue measure [5]. A subset A in Ω is called measurable, if it can be assigned to a measure. In this case we call $\mu(A)$ the measure of A. This measure is always a non negative real number or $+\infty$. A Lebesgue null set is a set $N \subset \Omega$ with the Lebesgue measure 0.

If $N \subset \Omega$ with $\mu(N) = 0$ and f is a Lebesgue integrable function, the following equation is valid:

$$\int_{\Omega} f \, d\mu = \int_{\Omega \setminus N} f \, d\mu + \int_{N} f \, d\mu = \int_{\Omega \setminus N} f \, d\mu,$$

since the integral over the null set N is equal to 0.

This theory will be applied for fleets of electric vehicles, starting with the description of one charging process of one EV. The EV with number i should be charged in the time $T_i = [t_{Arrival,i}, t_{Departure,i}] \subset \mathbb{R}^+$ with the energy amount $E_i \in \mathbb{R}^+$. This energy amount is chosen so that the EV will not charged more then up to its maximum battery capacity.

The charging function $L_i(t) \in \mathcal{L}^1(T_i)$ (space of Lebesgue-integrable functions) is valid when it ensures that the needed energy amount can be charged during the planed EV standing time at the respective charging station. Expressed as an integral this means: $\int_{T_i} L_i(t)dt = E_i$.

Furthermore for each EV i we need to make sure that the technical constraints given by the EV and the used charging station like the maximal charging power $P_{max,i} \in \mathbb{R}^+$ and the minimal charging power $P_{min,i} \in \mathbb{R}^+$ will not be violated. The $P_{max,i}$ we use for the optimization resolves as the minimum, of the maximum charging power given by the EV, and the one given by the used charging station; $P_{min,i}$ is assigned similarly as the maximum of both given minimum charging powers. This ensures that no technical boundaries of the EV and the charging spot get violated. Therefore the charging plan L_i always has to respect the boundaries: $0 < P_{min,i} \leq L_i(t) \leq P_{max,i}$. When we also allow stopping the charging completely, the co-domain is given as: $[P_{min,i}, P_{max,i}] \cup \{0\}$. An example of such a charging plan with respect to the boundaries is shown in Figure 1.

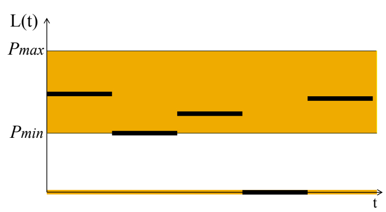

Figure 1. Example charging plan for an EV

In times of discharging, each EV and each charging station also has a maximum and minimum discharging power $P^{dis}_{max,i}, P^{dis}_{min,i} \in \mathbb{R}^-$. This leads to a co-domain for the charging and discharging curve L_i:

$$\left[P^{dis}_{max,i}, P^{dis}_{min,i}\right] \cup \{0\} \cup [P_{min,i}, P_{max,i}] \, .$$

This paper only considers charging of the EVs and not discharging, due to the fact that most EVs do not allow discharging yet. Furthermore it causes secondary losses by discharging and recharging again. Therefore this approach chooses to pause the charging in times of grid restriction as a more efficient alternative of providing positive load shift to the grid.

The considered charging function is discrete, which means that the time interval $[t_{j-1}, t_j)$ with a certain length (e.g., 15 minutes) has a constant charging power $l_{i,j}$, and can be written as:

$$L_i(t) = \sum_{j=1}^{n} l_{i,j} \cdot 1_{[t_{j-1},t_j)}(t).$$

With the help of this discretisation the charging function can be described as a vector:

$$\vec{L_i} = \begin{pmatrix} l_{i,1} \\ l_{i,2} \\ \vdots \\ l_{i,n} \end{pmatrix} \in \mathbb{R}^n.$$

Having described the charging plan, we can now consider the cost function K which is a piecewise constant in the same discretisation as the charging plan:

$$K(t) = \sum_{j=1}^{n} k_j \cdot 1_{[t_{j-1},t_j)}(t) \Leftrightarrow \vec{K} = \begin{pmatrix} k_1 \\ k_2 \\ \vdots \\ k_n \end{pmatrix} \in \mathbb{R}^n.$$

The optimal charging function regarding the cost L_i^{opt} is then given by the following optimizations problem

$$L^{opt}(t) = min_{L_i(t)} \int_{T_i} L_i(t) K(t) dt$$

or vectorial written:

$$\vec{L_i}^{opt} = min_{L_i} \vec{L_i}^T \vec{K}.$$

For a fleet of m EVs, we can now describe the scenario as the following optimization problem:

$$\begin{pmatrix} l_{1,1} & l_{1,2} & \cdots & l_{1,n} \\ l_{2,1} & l_{2,2} & \cdots & l_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ l_{m,1} & l_{m,2} & \cdots & l_{m,n} \end{pmatrix} \cdot \begin{pmatrix} k_1 \\ k_2 \\ \vdots \\ k_n \end{pmatrix},$$

where for each EV_i the following constrains must be valid: $l_{i,j} \in [P_{min,i}, P_{max,i}] \cup \{0\}$ and

$$\int_{T_i} L_i(t)dt = \int_{T_i} \sum_{j=1}^{n} l_{i,j} \cdot 1_{[t_{j-1},t_j)}(t)dt = E_i.$$

The last important constrain for this scenario, is that the load limits from the grid $NK(t)$ in each time-interval must not be exceeded. This means that for each j and time interval $1_{[t_{j-1},t_j)}$ the following equation must hold:

$$\sum_{i=1}^{m} l_{i,j} \cdot 1_{[t_{j-1},t_j)} \leq NK([t_{j-1}, t_j)).$$

If we simplify the technical restrictions of the EV and don't allow complete stopping of the charging, our range $[P_{min,i}, P_{max,i}]$ is convex and we receive a linear optimization problem. However, by adding the point 0 to our range, it is no-more convex and we have to deal with a more complex non-linear optimization problem. We now can model this as an mixed integer non-linear problem by adding two additional parameters $x_{i,j} \in \{0; 1\}$ and $y_{i,j} \in [0; (P_{max,i} - P_{min,i})]$ for each i and j. With this our charging function can be expressed as: $l_{i,j} = x_{i,j} \cdot (y_{i,j} + P_{min,i})$.

This mathematical description leads to a non-linear optimization problem with two types of constraints i.e., hard and soft. The hard constraints, must not be violated. In practice for our investigation, these are the grid capacity and the charging power of the EV and the charging spot. The grid capacity is not allowed to be exceeded, otherwise it may cause blackouts. The enforced charging power of the EV has to follow the EV and charging spot specific parameters. This means that the charging power for one EV has to lie between the minimal and maximal charging power of this EV and the charging spot or zero when charging is being paused. The soft constraints which in practice for our investigation depict the desired state of charge (SOC) at the end of a charging process. In exceptional cases – when not enough capacity is available – the system cannot ensure that this state of charge will be reached. In extreme cases when grid loads are too critical, EVs have to be rejected. In these cases the concerned fleet operator receives information on possible alternative charging options (e.g., longer standing time, a lower state of charge for the charging process, a different charging location etc.). This EV will be selected by the algorithm to ensure the best possible solution where the most EVs can be charge to fulfill there business purpose.

III. Algorithm

For the intelligent charging plan algorithm we use an evolutionary algorithm whose general process [6] can shortly be described by these steps:

1) Select a start population of individuals randomly or partly randomly (first generation).
2) Analyze the fitness of each individual in that population.
3) Choose the most healthy individuals for reproduction (parents).
4) Generate the next generation of individuals through crossover and mutation operations.
5) Analyze the fitness of each individual of the new generation.
6) Substitute the least-fit population with individuals of the new generation.
7) Iterate this evolution process (step 3-6) until the criteria for termination is reached.

This process is adopted in the use case of EV fleets by choosing a new specific representation for this model and adjusting the standard operations for crossover and mutation to it. Furthermore it is combined with methods from scheduling, in order to select the starting population and introduce a new measure that describes the flexibility that each EV has according to its operational utilization plan. How this is done, is described in the following sections.

First, to charge an EV i in time T_i with a requested energy amount E_i, a discrete charging function $L_i(t)$ is calculated with constant values for each time interval e.g., 15 minutes, taking into account parameters from the energy market. The representation of a solution is described as a permutation of the EVs with an additional value for the maximal charging power $P_{max,i}^{rep}$. This represents the chronological order in which EVs are optimized and the maximal charging power represents the maximal power each EV is allowed to charge in each time interval. This maximal power is not necessarily the same as the one given by the technical restrictions. This randomly chosen maximal power, which is always in the interval of $P_{min,i}$ and $P_{max,i}$ given by the specific parameters of the EVs and the charging spots, has to be high enough that the EV can reach its requested state of charge in the specified time period.

Subsequently, each EV sets itself an optimal cost with a greedy approach, considering its new given maximum charging power. One benefit from this approach is that the algorithm for optimal setting of each EV can easily be replaced with another algorithm without changing any other operators used in the evolutionary algorithm. In the start population, random orders of EVs and the random maximal power are chosen as aforementioned.

Some of the solutions in the initial population are generated with random maximal charging powers, as well as with the actual P_{max} given by EV and charging spot. To determine the order of the EVs, possible selection methods from scheduling are used: One is based on the predicted departure time, which means that the EV that leaves first gets set first. A second possibility is to select the EVs by their requested energy amount, where the EV with the highest energy request is set first.

A more complex approach (but still with the two options for the maximal charging power) is to sort the EVs by their flexibility. To calculate the flexibility, the following formula is used: $\frac{E_i}{\int_t P_{max,i} dt}$. This represents the quotient of the requested energy amount divided by the maximum energy that the EV can charge in its standing time.

As a one-point-crossover operator for our representation we choose a random crossover point and keep the first part of each solution. The missing EVs in this permutation are used in the same order as in the other solution. As a mutation operator we use a swap mutation operator. This means, that we choose randomly two points of the permutation and switch them. These EVs can then set themselves again in the new order and choose a new maximum charging power. Another option for a mutation operator is to choose randomly two numbers of the permutation and switch them; then set them again in the new order but with the old maximum charging power. The third option is to choose randomly two numbers of the permutation and only select a new maximum charging power, without switching the order. To ensure efficient mutation, only EVs with overlapping charging time are switched and EVs without flexibility cannot be shifted. After this recombination and mutation process each solution is evaluated.

For each solution we measure the overall cost which includes the energy price as well as penalty cost for the rejection of EVs or violation of the operation plan which is expensive (e.g., 1000 times the maximum energy price). Furthermore for different use cases we can include additional penalties like too many interruptions, irregular charging or the circumstance that priority EVs are not prioritized. For the selection algorithm a best selection is used. The idea here is to select the fittest individuals of a generation and leave them unchanged in the next generation. But of course the same algorithm would work with a more complex selection strategy like e.g., tournament selection.

IV. Evaluation

A. Use Case: DHL fleet

The challenge of the energy management we pursue, is to satisfy all constraints e.g., minimize the electrical energy costs for the fleet, avoid the violation of the load limitation curve, and respect the technical restrictions of each EV. This means that the energy management system has to calculate the optimal charging plan for each EV with respect to the cost for the entire fleet. For this the energy management system has to use data from the energy market, the EV and the fleet operator. An overview of the system with all the necessary interfaces is depicted in Figure 2. The necessary data is collected from the technical parameters of each EV, the EV fleet operational schedule, the (forecasted) electricity price curve, as well as the load limitations for a specific period of time e.g., 24 hours. With this data the algorithm will calculate a cost optimal charging plan for the fleet that respects the constraints of the fleet operator, the EVs and the energy market. This charging plan is then communicated to the charging stations, which enforce it and control the charging of the EVs.

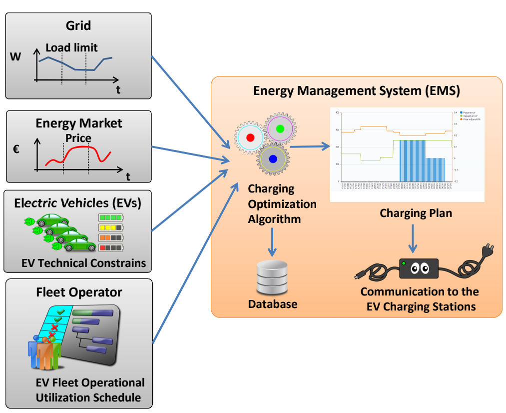

Figure 2. Overview of the Energy Management System and its interactions

As proof of concept, we focus on a real-world use-case i.e., we look at fleets of EVs which can be found usually in enterprise environments. The fleet of the German parcel and post service DHL is taken here as an example. The DHL fleet is a good example for a fleet with high predictability. The fleet schedule follows two groups with different departure times. The first group leaves between 07:35 and 07:45, the second one leaves between 08:45 and 08:55. The arrival time for both groups lies between 16:00 and 18:00. In average they drive 50–60 Km per day;this makes them an ideal case for electric vehicles [7].

The orientation for the technical data of the EVs was the e-Vito with a maximum range of 130 km, a battery capacity of 36 kWh and a charging time for complete recharging of 5 h [8]. Based on this fact-sheet, we choose choose 30% of the EVs a maximum charging power of 6 kW and desired energy amount of 20 kWh, 30% with 7 kW and 24 kWh and 40% with 9 kW and 32 kWh for the 40 considered vehicles. The minimum charging power for all vehicles is set to 2.3 kW.

For the capacity boundary for the fleet first a constant grid capacity minus the standard load profile of average households [9] is used, and as a second approach real-world data is used from renewable energy sources like wind production. This generation datasets for wind refer to a single location in Spain as collected by the NOBEL project [10]. To calculate the energy production from the wind data, we used the model for the “Tornado 1 kW” turbine. According to [11] 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 example day 02-Oct-2013 was chosen from the dataset.

In this DHL scenario, EVs are treated equally and it is considered that the 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 the EVs are charged at least at the level the fleet operator wishes at the end of the charging session. Failure to do so would imply that the EVs would not be operational and can not fulfill their business purpose, which would result in higher cost. Besides the constrains set by the fleet operator, we also consider the technical boundaries of each EV e.g., battery capacity. Additionally the grid and the energy market have some influence in the charging plan, as a variable price profile for one day and grid load limit curves are obtained.

B. Assessment

In literature there a several publications [12], [13] that consider complex battery models and model the charging of a fleet as a linear model. For instance optimized charging and discharging for an EV fleet is presented, as well as a framework for this optimization using a linear programming approach by assuming a continuous interval between the maximum discharging and charging from the battery is demonstrated [14]. In another approach [15], an algorithm builds on the inhomogeneous Markov model to optimally decide when to charge an EV can be used to schedule the charging. Others [16] have also used an improved particle swarm optimization algorithm to reduce the operational cost of the power grid while meeting the EV owner’s driving requirements. An evolutionary algorithm to integrate a single EV in a smart home environment has also been investigated in that context [17]. In this work, we also use, as already discussed, an evolutionary algorithm to optimize the charging for an EV fleet by considering the given EV restrictions, that collectively lead to a non-continuous interval for the allowed charging power.

Due to this non-linearity present, we are not able to use standard mixed-integer linear programming solvers like IBM CPLEX, Gurobi, and Xpress. Methods like Branch-and-Bound are also available in some of these libraries but they have a long execution time, as it was shown for an energy management case in a smart home environment [18]. Hence this is not attractive for our use case, where we target low execution times. Therefore we used the algorithmic approach as described in section III, to solve the optimization problem and evaluate it for the example case of the DHL fleet.

For the parameters used in the algorithm, a standard suggestion is used [6], advising that the population size lies between 1 and 30 solutions and the best selection for the quotient between parents solutions and number of solutions in the evaluation of the fitness has a value between $\frac{1}{5}$ and $\frac{1}{7}$. In this case this leads to a start population of 20 solutions and in each evolution process 40 child individuals are generated with recombination and 40 with mutation. For the next generation, the 20 best solutions are selected, and this is repeated for 1000 generations.

The experiments show that the first two scenarios tend to start with a good fitness which marginally increases. This is due to the fact that the start population is already generated with an intelligent approach, based on scheduling strategies and that enough capacity is available. In the third scenario (as depicted in Figure 5) the capacity is scarce and the first populations start with poor fitness, which however 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 then 0,1%) after the 500^{th}–1000^{th} generation. The execution time for the algorithm with 500 generations can be realized within less than 20 seconds. With this short run-times we can afford to let the optimization run for 500 generations even though it does not improve the end result significantly. Therefore in this work we decided for a longer optimization time (approx. 20 sec), but still have the option of shorter run-times (few seconds) if mandated by the requirements of time-sensitive scenarios. Experience from the 100 and 1000 generation experiments have shown that the run-time of the algorithm behaves approximately linearly by scaling the numbers of the EVs from 40 to 200 in steps of 40 EVs.

Figure 3 depicts the resulting charging plan (denoted with the blue line) for a DHL fleet of 40 EVs. The green curve shows the available energy and is calculated as the constant capacity minus the standard load profile of households. The red line denotes the electricity price profile (which is common in all tests) ranging from 0.20 € – 0.28 € per kWh. Without the algorithm the vehicles start charging with full power as soon as they are plugged in. In Figure 3 we see that they exceed the grid capacity. This will cause problems e.g., black outs. One can see that a non-optimized approach is not viable,

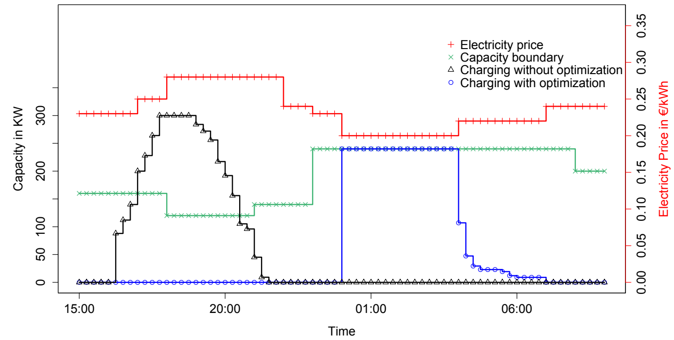

Figure 3. Charging plan for a fleet of 40 EVs

as the grid capacity is not respected and of course there is no cost optimization whatsoever. As depicted in Figure 3, the grid capacity limit is respected, and additionally the charging is happening during the lowest cost (price curve shown in red) slot, which results in 25% lower overall cost for charging the whole fleet. On the contrary in the same graph the algorithm ensures that all EVs are charged. Additionally it shifts the charging to a cheaper time and respects the grid boundaries.

In our scenario we consider energy supplier and grid provider as two independent stakeholders. Therefore the price profile is not necessarily correlated to the wind profile, even though in future, especially in demand-response scenarios, this might be the case. This scenario shows that the algorithm can handle both possibilities. The first priority is to respect the grid restrictions and with the flexibility which is given (under these restrictions) the algorithm chooses the best and cheapest solution for the EV fleet. This set-up may allow the EV fleet operator to have 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 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 [4].

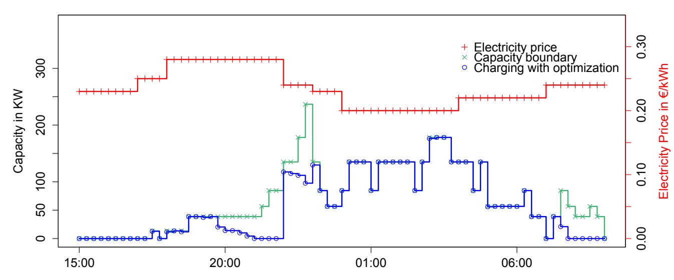

Figure 4. Charging plan for a fleet of 40 EVs with restricted grid capacity due to limited wind production

In Figure 4 the capacity boundary is now determined by the dynamic wind production. It can be seen that the consumption

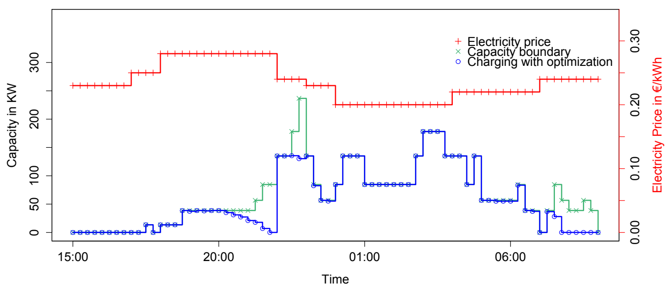

Figure 5. Charging plan for a fleet of 40 EVs with restricted grid capacity due to limited wind production and changes in the wind production

follows the production with respect to the optimization of EV charging i.e., the EVs are charged when surplus wind electricity is available and stop charging when there is no production. Furthermore the cheapest time slots with available wind production are selected by the algorithm. In Figure 4 we see the charging plan which was calculated with prior communicated wind production. Due to uncertainties in the wind forecast the wind production was updated with a more precise forecast 4 hours before the change. The algorithm calculates quickly a new charging plan and shifts the missing load to earlier times. The new charging plan is shown in Figure 5. The short run time of the algorithm shows that it can react on dynamic changes and that this scenario would work even for changes that are communicated for the next 15 minutes interval.

V. Conclusion

Effective management of the charging of EV fleets may provide tangible benefits for its owner, while in parallel adhering to dynamic conditions such as grid capacity, RES availability, cost effectiveness etc. The charging scheduling problem is formulated as a load management system, that leads to a mixed integer non-linear programming problem, solved by an evolutionary algorithm. Due to the simplifications we make, low execution time is achieved for the construction of an adequately for the real-world optimized charging plan. As such we can execute the optimization often in order to accommodate dynamic changes in the constraints given e.g., change in grid capacity, EV presence, electricity cost etc. Experiences show that the run-time of the algorithm behaves approximately linear depending on the number of generations as well as size of the fleet. As proof of concept we have simulated the charging plan for 40 EVs based on real-world data and demonstrated the effectiveness of the approach. Next steps will focus on more in-depth evaluation of the algorithm, with varying scenario constraints and an increased number of stakeholders that interact. Another option for future work is using the possibility of the algorithm to adjust on dynamic changes to participate in demand response or demand side management. Furthermore we can select different recombination and mutation operators within the algorithm to compare the performance operators. The real word scenario can be expanded to bigger fleets and different use cases.

Acknowledgment

The authors would like to thank the European Commission and the German Federal Ministry of Economic Affairs and Energy for their support, and the partners of the SmartKYE (www.SmartKYE.eu), open ECOSPhERE (www.ikt-em.de/de/openECOSPhERE.php) and eBadge (www.ebadge-fp7.eu) projects for the fruitful discussions.

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