

Metaheuristic Optimization of Electric Vehicle Charging Strategies in Uncertain Environment

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Abstract—Probabilistic power flow studies form essential investigations for both operation and analysis of electric power grids under stochastic conditions. Especially the increasing penetration of intermittent and non-dispatchable power plants like wind power plants cause probabilistic behaviour at the supply side. At the same time, the expected penetration of electric mobility at the demand side complicates this situation further. Their optimal coordination is of major concern for future smart grids, which represents a highly challenging topic caused by its nondeterministic nature. Therefore, a simulation-based framework will be presented, that uses metaheuristic optimization algorithms for computing charging strategies of an electrified car fleet. These strategies will be capable of both satisfying energy demand of electric vehicle users and considering physical operation constraints of the distribution grid while optimizing some objective function like financial costs of energy supply. The central idea is the application of simulation for evaluating the fitness of a solution candidate generated by the metaheuristic optimization algorithm. During evaluation, each candidate will be sampled a sufficient number of times in order to overcome uncertainty of the stochastic system which is represented through simulation.

Index Terms—Electric Vehicles, Charging Control, Simulation-based Optimization, Metaheuristics

I. INTRODUCTION

Increasing penetration of electric mobility will cause new operation conditions to power grids which will have to be investigated in order to guarantee reliable and secure power supply in the near future. Even if the energy demand of those vehicles can be satisfied with existing free capacities during periods of low demand, temporarily occurring peaks in power demand caused by an electric fleet may lead to critical operation points. Numerous investigations show the necessity of control strategies for charging of electric cars [1] [2] [3], which is a challenging task due to the stochastic nature of individual behaviour. Additionally, an increasing share of zero-emission power supply forces the penetration of intermittent power plants like wind power or photovoltaics. Their non-dispatchable, weather-dependent and therefore non-deterministic power output further complicates the situation in power grids from the supply side. The combination of electric mobility and probabilistic supply is therefore a highly interesting field [11], which will be the central topic of this

work.

In different areas concerning planning and operation of electric power grids, probabilistic load flow studies serve as central tool for computational consideration of stochastic influences. Therefore, a simulation-based optimization approach will be shown that uses metaheuristic algorithms for computing optimal charging strategies of an electrified car fleet that both satisfy energy demand of individual car users as well as incorporate the physical characteristics of the electric power grid under the special condition of partly probabilistic supply. Since the power grid will be considered through load flow simulations, constraints can be considered that ensure reliable operation.

The rest of the paper is organized as follows: chapter two introduces some basics of optimization in power grids and the special task of integrating electric mobility while maintaining an overview of related work, also the principles of simulation-based optimization will be shown. Chapter three goes more into detail with the simulation model that represents both, the power grid as well as the individual traffic within interrelated components. Subsequently, chapter four describes the real-world application scenario as well as the problem that has to be solved. In chapter five, results will be discussed which lead to final conclusions in chapter six.

II. OPTIMIZATION IN POWER GRIDS

A. General Overview

Optimization plays a central role within planning and operation of electric power grids. The computation of optimization tasks like optimal power flow, economic dispatch or unit commitment [5] [6] build essential features in modern software tools that are applied in energy industry and research. Beside conventional deterministic methods like optimization using the Lagrangian or algorithmic approaches as linear or quadratic programming with different specific methods [5], heuristic algorithms progressively come to the fore within this field [6] [7]. Here, the computation of electric vehicle charging strategies forms a new optimization task that challenges the investigation of innovative approaches.

B. Optimal Integration of Individual Electric Mobility

Various researchers examine the problem of integrating electric cars optimally into power grids. The main idea is that some kind of central or decentral control influences the individual charging behaviour in order to avoid critical peak loads on the one hand, but to flatten the overall load curve on the other hand [4]. Thus, direct control of charging cycles is seen as advantageous for reaching optimal load profiles [1] [3] [8]. Central challenge beside the computation of the optimization problem itself is the consideration of the individual behaviour that mainly characterizes electric vehicle charging load. Different approaches try to tackle this task using static load profiles from statistical investigations [1], representations of behaviour using Queuing Theory [11] or simulation via Monte Carlo Methods [8]. All these approaches generally have in common that they try to compute static profiles of electric vehicle charging load that are later used within certain optimization methods. Thus, there is no interrelated process that incorporates probabilistic behaviour during the search for optimal solutions.

Especially when talking about optimization in uncertain systems, simulation-based optimization with heuristic algorithms has been applied to various fields of applications, since this approach is capable of fully considering dynamics as well as the stochasticity of such systems within the process of optimization, being the main concept used here. With this optimization concept, complex systems can be tackled that cannot be formulated by closed-form mathematical representations, but need to be modeled with simulation. Here, metaheuristic algorithms search for optimal parameters within simulation models. This search-process therefore describes a directed and intelligent search, using nature-inspired strategies for exploring promising regions within the solution space. Similar to [9], simulation will be used as representation of individual traffic behaviour, where discrete event simulation is substituted with multi-agent simulation with the aim of decreasing computational effort.

C. Simulation-Based Optimization

This approach has already been presented in [7] for the general purpose of optimization in electric power grids and in [10] for the specific application of solving the optimal power flow for a benchmark problem. The central idea is the application of simulation for evaluating the fitness of a solution candidate generated by the metaheuristic optimization algorithm. Within this work, the solution represents the charging strategies of an electric car fleet for a specific time interval. During evaluation, each candidate will be sampled multiple times in order to overcome uncertainty of the stochastic system which is represented through simulation. Therefore, Matlab will be used for simulation, where “MatPower” [12] serves as simulation toolbox for power flow calculations. Additionally, the open source software “HeuristicLab” [14] [15] that features usage, development and analysis of numerous metaheuristic algorithms, is applied for optimization, where Matlab serves as plug-in for an external evaluation problem.

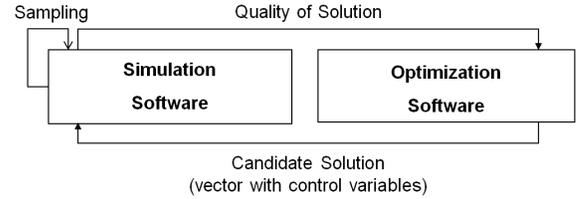


Fig. 1. Process Flow

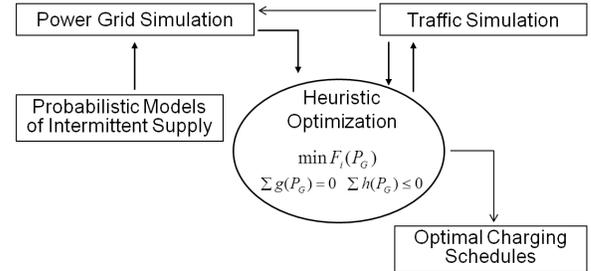


Fig. 2. System Architecture

The processflow of simulation-based optimization is indicated in Figure 1.

Since in this case a stochastic system is represented with simulation, evaluating the same solution candidate multiple times will lead to different outputs respectively different fitness values. Therefore, sampling is used, where each solution candidate is evaluated multiple times, where the resulting fitness value is averaged in order to get an estimate of the candidate’s performance in an uncertain environment.

III. PROCESS ARCHITECTURE AND SIMULATION-BASED SAMPLING

The architecture of the used optimization framework respectively its interrelated components is specified in Figure 2.

Within the architecture, the optimization component serves as master that initiates the simulation components for evaluation of the proposed candidate solution. The following steps will go more into detail with the single components.

A. Power Grid Simulation

For considering the electric power grid through power flow calculation, a modelled distribution grid implemented with MatPower is used. The computation of the power flows is necessary for considering physical distribution grid constraints and therefore evaluating the feasibility of a solution on the one hand, but for computing the resulting power consumption of the system for fitness calculation on the other hand. A deeper description of constraints and the fitness function will be presented later. Principally, the power grid will be stressed following a base load profile caused by domestic, commercial and industrial consumers. For modelling probabilistic base load as existing in real world conditions, the profile will be randomised to a certain degree within each simulation run.

B. Electric Individual Traffic

Multi-agent simulation is used for the consideration of individual traffic, which is necessary in order to model at which time single cars will be parked and ready for charging on the one hand, but further for evaluating if each single car received the demanded energy on the other hand. Therefore, for each agent in the system, a synthetic driving behaviour will be simulated that represents time interval and location (i.e. bus in the distribution grid) of being parked and plugged to a charging infrastructure. Real-world data about driving behaviour is used as essential information for the simulation model that is taken from an official survey by the Austrian ministry [16].

C. Intermittent Supply

Within probabilistic power flow studies, intermittent sources like wind power or photovoltaic power plants are generally modelled using probability distributions. Within this work, exemplary wind power plants will be considered. For simulating their power outputs, within each simulation run the expected wind speed is sampled from a Weibull-distribution. With this resulting wind speed, the corresponding power output can be computed using the plant's power curve ¹.

D. Optimal Charging Strategy

The solution to the optimization problem is a real-valued one dimensional vector that defines the desired charging power for each single car during a specific time slot. This charging strategy therefore not only satisfies the charging demand of each single customer, but additionally considers physical constraints of the distribution grid while minimizing some cost function. The scheduling-horizon therefore is chosen to be 24 hours, i.e. the strategy defines the desired charging behaviour over a whole day for each car.

IV. APPLICATION SCENARIO DATA AND FORMULATION OF THE OPTIMIZATION PROBLEM

A. Simulation Data

In order to guarantee universality for the considerations within this work, the well known IEEE 14-bus² testcase will be applied and adapted for forming a suitable power grid model. 960 individual electric cars are being simulated, each single car can produce a charging load of maximum 11kW, related to a three-phase charging process with 400V and 16A, as exemplarily possible when using a Mennekes VDE (Type 2) plug connector [17]. This configuration, as existing for example when charging the well known Tesla Roadstar, is certainly one of the most important technical specifications in this field in actual developments. In reality, various configurations can occur, but using this single specification is valid for the underlying simulation model. The power grid simulation

¹The power curve describes the relation between the wind speed and the power output of a specific wind power plant considering its physical characteristics within a simple two-dimensional function

²14 Bus Power Flow Testcase, Power Systems Test Archive, <http://www.ee.washington.edu/research/pstca/>, Retrieved: 24.11.2011.

model is being downscaled such that the cumulated charging power of all cars sums up to 10% of the daily peak load maximally.

For representing individual electrified traffic from a power grid point of view, as discussed above, the relevant behaviour that has to be modelled describes time interval and location of each single car when being parked and connected to a charging infrastructure. Based on real-world data from an Austrian survey [16], two most relevant driving patterns can be extracted for a week day, namely the pattern of full-time and half-time workers. Within each pattern, three different locations are modelled for parking at home, at work and at any location in free time (shopping, education, entertainment). For each location, different probabilities for the existence of a charging infrastructure are modelled, describing a possible future infrastructure from an actual point of view: at home, each e-car user has an own charging station. At work, there is a probability of 50% that an appropriate infrastructure is available. For locations where potential users remain in free time, this probability is assumed to be 25%. The resulting charging load at a specific location is than being correlated to a corresponding bus within the power grid model. Within each simulation run, synthetic driving profiles are computed from prototype-profiles, being randomized in terms of driving time and remaining time at specific locations. Thus, the probabilistic behaviour of individual traffic can be modelled based on real-world data and incorporated into the metaheuristic optimization process enabled by the simulation-based approach. For modelling the power output of renewable sources, a wind power plant is added to two busses in the network. Therefore, the corresponding wind speed values at the plant sites are sampled from a Weibull-distribution as described in [11], where their power curves are adapted such that each plant reaches an output of 5 MW at cut-off windspeed. The randomisation of the base-load profile is realized through multiplying each discrete value of a given profile with a normal distributed random sample from the distribution $N(1,0.016)$. Here, an average residential load profile in the EU-27 member states is taken from [18].

B. Description of the Optimization Problem

1) *Restrictions:* As already mentioned, within this optimization problem there exist two different fields of restrictions, namely restrictions that ensure safe power grid operation, and those that guarantee satisfaction of energy demand of electric vehicle users.

From the power grid point of view, restrictions from the general optimal power flow problem (OPF) formulation are taken [5], consisting of equality and inequality constraints. The set of inequality constraints includes lower and upper bounds for variables to assure stable operation, for instance the generation capacity of each generator, that is restricted to a certain range: $P_{G_j}^{min} \leq P_{G_j} \leq P_{G_j}^{max}$, for $j = 1, \dots, J$, and the upper limit of the power flow through transmission lines: $P_l \leq P_l^{max}$, for $l = 1, \dots, L$, with J being the total number

of buses and L being the total number of transmission lines. Additionally, there exist lower and upper bounds for the resulting voltage deviation at each bus: $V_j^{min} \leq V_j \leq V_j^{max}$, for $j = 1, \dots, J$. Since the optimal power flow is not solved within this work, which means that the output-power values of the generators cannot be decided, the only constrained generation bus is the slack bus. The slack bus [5] is adapted during the power flow calculation such that the power balance is guaranteed. So, for example, if there would be a high charging load at peak time hours, the slack bus would have to take a high output value that violates its constraint. Using this slack-bus method for power flow calculation (which is the standard method), power balance is ensured implicitly. Since power balance would be the only equality constraint, no such constraints need to be considered. All the lower and upper bounds are taken from the IEEE 14-bus testcase.

In order to guarantee feasibility of solutions from the electric car fleet point of view, different restrictions have to be satisfied as well which can be stated as inequality constraints: at the end of the scheduling horizon, the energy demand of each single car has to be satisfied, stated as $\sum_{t=T}^{24} P_t * \Delta t \geq E_{min}$ for each car. Therefore, the sum of charged energy over all discrete time steps has to satisfy a minimum. E_{min} is defined to be 10 kWh, which corresponds to a driving range of 50 kilometers per day with a mean consumption of 0.25 kWh/km, as can be considered as average value for actual market-available electric cars like for instance the Mitsubishi i-MiEV. Δt is defined to be 1 hour.

2) *Objective Function:* Since both safe power grid operation as well as fulfillment of end users energy demand are guaranteed through constraint satisfaction, the objective function can consider financial costs of energy supply. While power production within the distribution grid cannot be influenced, all additional power comes as input from the slack bus and therefore probably from another power grid area. The financial costs of this additional power should be minimized, therefore using spot market price data from the European Energy Exchange [19] seems to be a suitable approach. The daily price profile of hourly contracts has been averaged over 5 working days from 19.9.2011 to 23.9.2011, building an appropriate basis for the minimization of financial costs. This approach leads to the additional benefit, that spot market prices usually run similar to the daily load profiles, which causes the optimization process to force electric charging during time steps of low load. Since constraint satisfaction is considered using the concept of penalization, the final fitness function can be stated in equation 1 as aggregation of objective function and constraint violation. The daily load profile relative to the peak load as well as the electric energy spot market prices are shown in Figure 3.

3) *Control Variables:* As stated above, the solution describes charging strategies for all cars. Therefore, a strategy consists of the real valued charging power in $i = 24$ discrete time steps, each being a single control variable. Since computing such strategies for all 960 electric cars in the

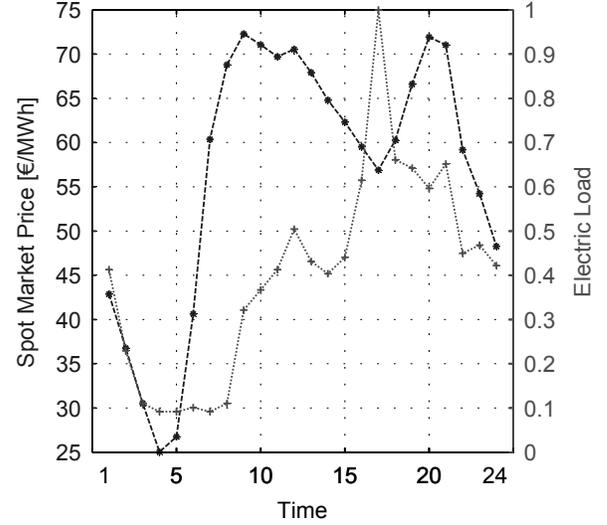


Fig. 3. Energy Prices and Base Load Profile

system, $960 * 24$ control variables would be needed, yielding in a typical case of state space explosion. So, electric cars that have similar charging patterns and exist in equal regions of the power grid, get clustered to a group size of 60, hence, reducing the state space to $16 * 24 = 384$ dimensions, which is a manageable problem size for metaheuristic algorithms. Further, using clusters leads to an averaging effect, that satisfies individual needs of each car within a cluster, while maintaining some tolerance between individual energy demand and scheduled charging supply. Thus, if the proposed charging strategy for all cars within a cluster would not satisfy the demand of a single car, the resulting constraint violation would penalize this strategy. Additionally, further investigated systems may offer a much higher number of electric cars, therefore, using clusters provides the only feasible strategy. In the end, the vector of control variables can be stated as one-dimensional real valued vector $P_c = [P_{c1,1} \dots P_{ci,n}]$ for $n = 16$ clusters.

The resulting fitness is stated as:

$$\text{Minimize} : \sum_{i=1}^{24} [C_f(P_C) + W * CV(P_C)], \quad (1)$$

where W is a vector consisting of constant multipliers that determine the weight of each single constraint relative to the cost function. CV defines the violation of each single constraint, arranged in a vector.

Summing up, the constrained optimization problem is approximated through a nonconstrained one by adding some penalty function that punishes the violation of constraints. The computation of the violation itself as well as the computation of the objective function are performed within the simulation run.

For presentation reasons, the general processflow where the interactions of the single components can be identified is shown in Figure 4 using a flowchart. The metaheuristic

algorithm is abstracted within a single box in order to highlight that the general approach works with each algorithm of this type, further details about the used algorithm are presented in the next chapter. A general explanation about this class of algorithms cannot be offered within this work, but can be obtained within the technical literature [13].

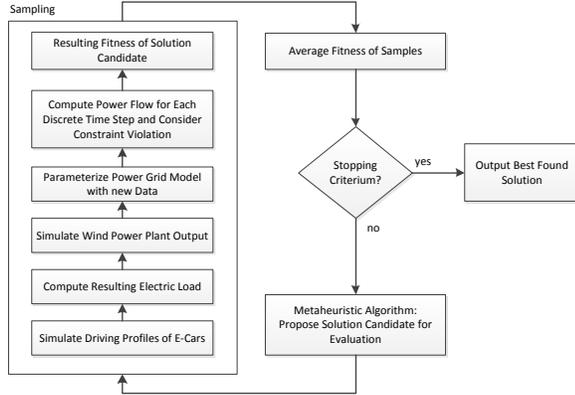


Fig. 4. Flowchart of the Optimization Process

V. EXPERIMENTAL RESULTS

Various algorithms already implemented in HeuristicLab have been tested on this problem. Finally, Evolution Strategies (ES) [20] performed best with the parameterization shown in Table I. In principle, ES is a nature-inspired population-based optimization algorithm, that tries to improve a set of solution candidates until a certain stopping criterion is reached. Contrary to other related algorithms, ES selects the best individuals within each generation and improves them where mutation is the main evolutionary operator. It is generally proven to be a powerful and efficient metaheuristic algorithm for real-valued optimization problems, supplied by its special ability of self-adaptiveness within the search process. A detailed description of the parameters can be found in HeuristicLab [15] respectively the appropriate literature [13] [14].

TABLE I
PARAMETERS EVOLUTION STRATEGY

Type	(20 + 40)-ES
Manipulator	SelfAdaptiveNormalAllPositionsManipulator
Recombinator	AverageCrossover
Parents per Child	2
Stopping Criterion	Maximum Generations: 5000
Sampling	Sample Each Solution 6 Times

The best achieved result is presented in Figure 5, plotted as mean charging strategy over all 960 electric vehicles within the simulated system. For better indication of this approach, a hypothetical load is indicated by the grey bars that would result in average if all simulated vehicles would be plugged to the power grid and start charging immediately and uncontrolled after arrival at home without consideration of any constraints. The black bars show the average of the computed optimal

charging strategies, that both consider all constraints defined before and minimize the objective function. The advantages of the computed optimal strategy can be obtained directly: especially during peak-hours, the uncontrolled case would lead to a higher charging power starting at 12:00-13:00 when first half-time workers arrive at home, which additionally occurs around 17:00 as well, parallel to the daily peak load. Here, the intelligent charging strategy clearly tends to lower charging power and a shift of the charging processes to the night-hours. Especially at 17:00, the resulting average charging power of the uncontrolled case is nearly twice as high as in the controlled case. Sure, there occurs some charging power at this time, which is caused by the main reason that the used objective function indicated by the cost curve in Figure 3 leads lower prices at 16:00 und 17:00, which forces available vehicles to charge at this time as long as all constraints can be satisfied. Choosing another objective function that for example tries to minimize peak-load would lead to a lower resulting charging behaviour within these time steps. Another obvious fact is that the intelligent strategy schedules much more energy to the vehicles than they actually need, in average each vehicle would receive around 24 kWh. This is because of the aforementioned averaging effect that occurs because of the clustering of similar vehicles. Even if all vehicles within such a cluster show similar behaviour, individual probabilistic behaviour occurs. Thus, scheduling more energy as needed to each single vehicle allows such individual probabilistic behaviour while guaranteeing enough energy to everyone. Sure, from a power grid point of view, this behaviour is not optimal since free capacities cannot be used efficiently, but as long as all constraints are satisfied, this is absolutely valid. Another observation can be stated easily, namely that charging during night-hours is preferred by the intelligent strategy. This is caused by lower values of the used objective function during night hours on the one hand, but by the fact that most people are at home at this time where the probability of existence of an appropriate charging infrastructure is 100%, while this probability would be lower for other locations that are visited during the day time.

Taking some numerical results into account, the advantage of the intelligent strategy can be substantiated: if each car would charge the amount of energy that would be charged by the uncontrolled case with the computed intelligent strategies, costs of additional energy supply according to the spot market prices would come up to Euro 988.60. Considering the uncontrolled case, charging costs would amount to Euro 1168,90, which is around 18% more than with the intelligent strategies. Additionally, uncontrolled charging would lead to power flow constraint violation especially during time steps 17 and 18, which would make this scenario infeasible anyway. Thus, intelligent strategies are proven to be necessary within the investigated system.

VI. CONCLUSION

A simulation-based approach has been presented that is used for computing optimal intelligent charging strategies

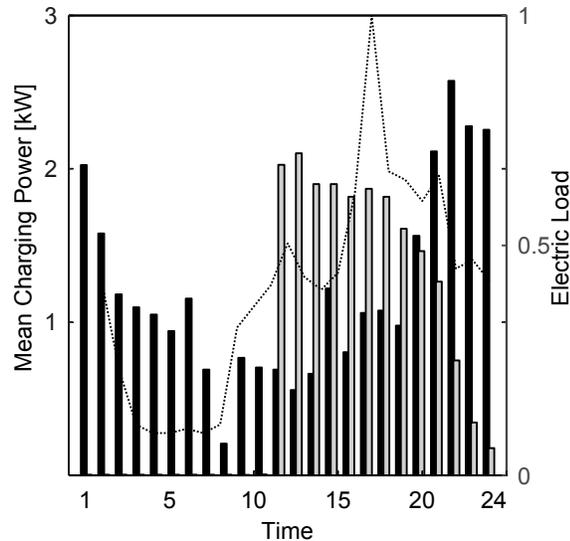


Fig. 5. Resulting Mean Charging Schedule

for a fleet of electric individual vehicles that exist within a distribution grid. The special ability of this approach is that through simulation the probabilistic influences of both individual behaviour as well as intermittent energy supply can be incorporated during the optimization process. In the end, intelligent strategies have been found that satisfy operation constraints from the electric power grid point of view while supplying energy demand by individual vehicle users. For comparison reasons, the strategy has been analyzed related to a case of uncontrolled charging, where clear advantageous results can be identified. From a practical point of view, this approach could be applied to two different use-cases: the first would be, as approximated within this work, the computation of optimal charging strategies for a real-world electric vehicles within a system. The second would be the usage for analysis reasons, for example investigations of whether a hypothetical electrified fleet could be supplied by a given power grid under optimal control or not. A high variety of application scenarios could be investigated therefore in order to analyze the near-future of electric mobility.

VII. ACKNOWLEDGMENT

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