Heuristic Power Scheduling of Electric Vehicle Battery Charging based on Discrete Event Simulation

Stephan Hutterer[1], Michael Affenzeller[1 2], and Franz Auinger[1]

[1] Upper Austria University of Applied Sciences
{stephan.hutterer, f.auinger}@fh-wels.at
[2] Josef Ressel Center Heureka!
michael.affenzeller@heuristiclab.com

Abstract. Since the electrification of individual traffic may cause a critical load to power grids, methods have to be investigated that are capable of handling its highly stochastic behaviour. From a power grid's point of view, forecasting applications are needed for computing optimal power generation schedules that satisfy end-user's energy needs while considering installed capacities in the grid. In this paper, an optimization framework is being proposed, that uses metaheuristic algorithms for finding these schedules based on individual traffic simulation using discrete-event methodology. Evolution Strategy implemented in HeuristicLab is used as optimization algorithm, where the used parameterization and the achieved results will be shown.

1 Introduction

As there is a general change from fossil fuels to alternative energies, this change takes place in the mobility- sector as well. Beside the electrification of the public transport which seems to be comparably easy because of deterministic schedules and fixed amount of routes, especially the electrification of the individual traffic causes manifold technical challenges. Here, various investigations have to be performed in fields like for instance power supply and power system operation, business cases for battery- usage, battery technologies and many others.
From a point of view of vehicle- development, different technologies will be needed on the way to a high penetration of electrification. Hybrid vehicles are already established in individual traffic since a couple of years. The next step is seen to allow charging the batteries of those hybrid vehicles via the electric power grid [1], which introduces the concept of plug-in hybrid electric vehicles. Not important which technology will lead to the final electrification of the car fleet, PHEVs serving as intermediate step or direct introduction of electric vehicles (EV) without internal combustion engine, what is for sure is that the electric fleet will cause an additional load to the power grid when batteries are getting charged. Considering this load, there exist general expectations that this will not be critical to the power grid since there is enough unused capacity in the

grids during off-peak periods that can be used for charging those batteries. But there is an important influence factor that has to be taken into account, namely the end-users that will have control of deciding when to recharge their cars. So they will tend to plug in when it is convenient for them, rather than when it's optimal for the power grid operation.

Handling such a fleet of pluggable vehicles requires control mechanisms from a power grid's point of view, in order to satisfy secure operation and optimal use of existing generation, distribution and transmission capacity. The development of such smart charging control strategies is a major challenge to future smart electric grids. By now, various control strategies have been investigated, mainly being classified as central and local strategies in order to guarantee controlled charging. Such control mechanisms have been introduced for instance by [2], [3], and [4]. All these strategies generally have in common that they are direct, which means that they use information like actual load in order to determine exactly the moment when to charge certain batteries. Another approach is to use a global energy market and real-time pricing to indirectly shift charging load. Here, the electricity price in off-peak periods will be relatively low to prices during peak-periods, which should bring end-users to plug-in their cars during off-peak times [5]. Nevertheless, direct control will have to be needed to a certain degree [6] since the stochastic behaviour of people may lead to critical operation points for the power grids. This control will not only be essential to simple load shifting in smart grids, but also to future vehicle-to-grid technologies [7].

Principally, in order to determine optimal control decisions for load shifting, information is needed about the amount of electrical power that is needed at a specific time. Since optimal strategies have to consider future power demand in a specific time interval, for instance over a day, static load profiles are used that have been generated from statistical investigations. Here, traffic- patterns are applied to derive the amount of cars that are plugged to the grid over time. Thereby the assumption is made, that each plugged-in car generates a specific charging load exactly at the time it is plugged to the electrical socket. But this assumption is a major caveat to the concept of load shifting since this concept means that after plugging in the car, a central control mechanism determines the exact time when the battery is getting recharged and thus a load to the grid is caused. So, the assumption that a charging load is generated immediately when plugging the car to the grid is not precise, since load shifting cannot be modelled accurately.

Additionally, these static load profiles generated from traffic patterns are incapable of taking the stochastic behaviour of people into account, which is a major task when trying to handle individual transport for determining decisions for optimal load control.

2 The Simulation-Based Approach

In order to come over these so defined challenges, a simulation-based approach is introduced that uses metaheuristic optimization algorithms to find optimal power schedules for charging cycles of an electric fleet. Therefore, a possible solution in form of a power schedule over a defined time interval is generated by the algorithm and then evaluated by a simulation run. The simulation- model therefore describes individual traffic behaviour and uses discrete- event simulation. This evaluation of a possible solution, the so called fitness of a solution, than is used to find better solutions until certain stopping criteria are fulfilled and a (near-) optimal solution is found.
With this approach, it is possible to consider the stochastic behaviour of individual traffic. Further, as central ability, load shifting can be modelled exactly since the simulation computes time intervals when specific cars are plugged to the grid and ready for recharge, and the generated power schedule specifies the exact time when they are charged and thus a charging load is generated.
The exact methodology and the used software- framework of this approach is described in [8] and now ported to traffic simulation. Here, a discrete- event model is created where the resulting electrical load caused by the electric car fleet is derived based on an Austrian study on traffic behaviour [9]. A realistic scenario of future penetration of electrified individual traffic will be investigated.
From a point of view of the optimization algorithm, HeuristicLab [10] [11] is used as generic framework for heuristic optimization. Since population- based methods are already proven to be suitable for high dimensional optimization problems in power system applications [10] [12], the suitability of this class of algorithms for the presented application is given.

3 Modelling Electric Mobility

For modelling load shifting, the simulation model has to describe the duration that a car remains in a parking lot, as well as the period it needs for charging its battery. For better understanding, the modelling approach is shown in Figure 1.

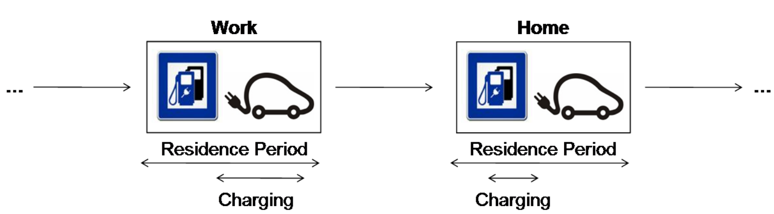

Fig. 1. Electric Mobility Model

Referring to the discrete-event simulation paradigm, entities are generated representing the cars in a system. Charging stations at parking lots at different locations are indicated by servers and queues, where the service time for an entity is its charging period, depending on the energy needed by a specific car and a probability distribution describing the uncertainty of individual traffic behaviour. For modelling realistic individual traffic behaviour, both individual routes as well as individual departure times have to be considerd. This information principally is taken from an Austrian survey on traffic behaviour [9]. Here, four different route- patterns are identified and finally modelled, that build around 80% of total routes, depending on regional properties, which seem to be enough for modelling the resulting load to the power grid:

Route Pattern	**Proportion relative to all routes**
Home - Work - Home	25%
Home - Shopping - Home	20%
Home - Off Time Activities - Home	18%
Home - Educational Institution - Home	17%

Table 1. Route Patterns

The individual departure times over the day, described by the relative amount of cars starting their specific route, is also taken from [9]. Since in realistic traffic behaviour, a car may has to leave the charging station before being charged completely, a time-out function has to be used that forces the corresponding entity to leave the server/queue it is remaining at, attaining into a sink measuring unsatisfied energy demand.

4 Formulation of the Optimization Problem

Control Variables
Since the aim of this approach is to find an optimal schedule for load shifting respectively an optimal schedule that describes the amount of energy that can be used for battery charging at a specific time step, the control variables represent the charging power of specific charging stations. Since determining the charging power for each single station in a defined distribution grid would be impractical, aggregators are used that cumulate charging stations of same type to one server in the model. Thus, the control variables combined with the needed energy of entities/cars add up to its service time.

Objective Function
Since the electric load straining power grids generally follows daily load profiles and peak load only occurs along relatively short time ranges, the objective of an optimal load dispatch strategy should be to optimally use free existing capacity and avoid additional peaks. The typical load profile over a day used in this paper is given in figure 2, also describing the optimization objective.

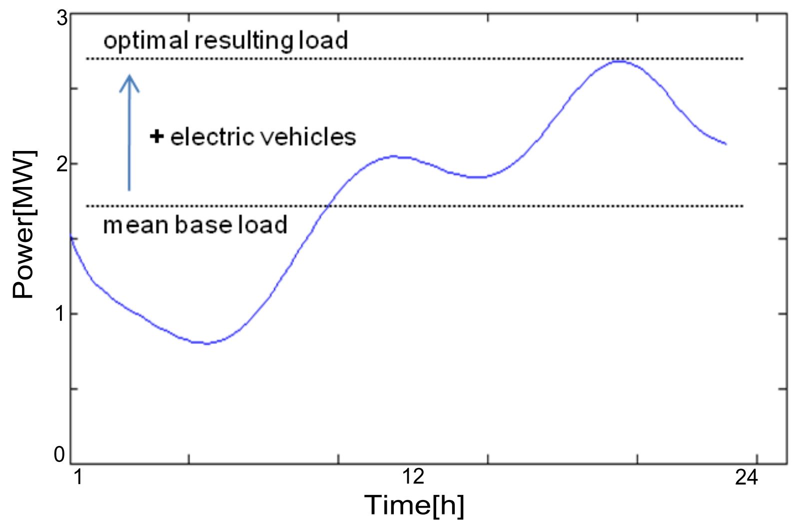

Fig. 2. Optimal Load Profile

The base load is given, having its peak around 19:00 p.m. The base load represents the electric load caused by residential, commercial and industrial consumers. Since the optimal load profile would be flat, the aim of load shifting generally is to flatten the profile. In this study, the base load cannot be influenced, but the load caused by charging of electric vehicles should be shifted in order to flatten the load profile while avoiding new peak loads. Thus, a candidate solution is a power schedule for charging stations over the day, where its fitness is the difference of the resulting load from the optimal load. The power schedule is represented by power values for 24 discrete time steps t=1...24. Thus, the fitness can be stated as:

$$\sum_{t=1}^{24} [L_{opt} - (L_B(t) + L_C(t))]^2$$

Here, L_{opt} is the optimal load being constant over time, L_b being the base load given in figure 2, with L_{LC} being the determined power schedule for electric vehicles charging, which is the candidate solution.

Consideration of Constraints via Penalty Term

Since the computed power schedule has to satisfy the needed power demand for charging all electric vehicles in the considered system, a constrained can be formulated stating that after a simulation run, i.e. after 24 time steps, all cars have to be charged. The satisfaction of this constraint is realized using a penalty term that is added to the fitness of a candidate solution, yielding a resulting objective function:

$$F(t) = \sum_{t=1}^{i} [L_{opt} - (L_B(t) + L_C(t))]^2 + r * (E_{uc}),$$

where E_{uc} is the needed but uncharged energy, cumulated over all cars during the simulation run.

5 Testcase

A test case is set up that is considering a residential area with 2000 households, where a relatively high penetration is assumed in order to show the abilities of this approach. The test case represents for each household in average 1.5 electric vehicles, which is a valid assumption for future 100% penetration of electric mobility. As heuristic optimization algorithm, Evolution Strategy (ES) is used. Since the computation time for evaluation of the fitness of a solution is in the range of seconds and thus relatively high compared to other optimization applications, low population sizes are used in such a case. Here, the following algorithm parameterization is used with HeuristiLab:

Parameter	**Chosen Value**
Children	3
Population Size	1
Parents per Child	1
Plus Selection	True
Maximum Generations	3000
Mutator	NormalAllPositionsManipulator
Recombinator	No Recombination

Table 2. ES Parameterization

Having defined the algorithm- parameterization, the following solution has been achieved as indicated in figure 3. Here, the dotted line shows the base load as defined also in figure 2. The computed optimal power schedule for the cumulated charging cycles of electric vehicles is represented by the thin line, while the resulting load caused by both base load plus electric vehicles is represented by the thick line. The computed schedule principally is a vector of 24 discrete power values, which in this case are interpolated for better illustration of the result. An arbitrary higher resolution of time steps could be used, however, this would lead to a higher number of control variables and thus to a higher dimensional optimization problem.

In the end it can be shown that reasonable schedules can be found that satisfy the general requirement of flattening the resulting load curve while minimizing new peaks. Sure, the peak load is exceeded to a certain degree, but due to the stochasticity of individual traffic this effect is unavoidable when supplying consumer demand. Depending on the installed power grid, this marginal violation of peak load will not cause critical operation due to the fact that most power grids are oversized to a certain degree for ensuring secure and reliable power supply.

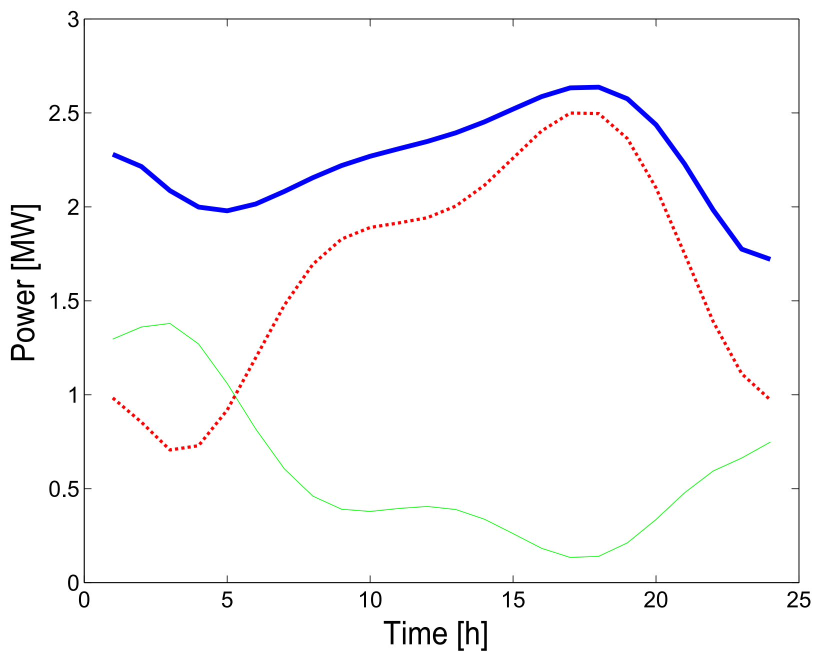

Fig. 3. Resulting Load Characteristics

6 Conclusion

In the end, a sophisticated approach is available that is able to derive power schedules that optimally fit to the individual traffic behaviour, considering stochastic influences and being able to exactly model load shifting. For a realistic test case, it has been shown that even for a high penetration of electric mobility, power schedules can be found that both satisfy consumer demand while optimally using already installed capacities in power grids.
As future perspective, this discrete-event traffic simulation will be aggregated

with continuous simulation of the electric power grid and builds a hybrid simulation-based optimization framework to consider both objectives and constraints from a power grid point of view and the end-user traffic as well, yielding into multi-objective optimization.

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